THE INFLUENCE OF LIFE TRANSITION PATTERNS ON THE CONTINuity AND CHANGE IN PSYCHOPATHOLOGY FROM ADOLESCENCE TO YOUNG ADULTHOOD AND THEIR PRECURSORS

by

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(Under the Direction of K.A.S. Wickrama)

ABSTRACT

The purpose of the present study are to address two hypotheses: (1) the additive and multiplicative effects of early contexts and individual characteristics on the life transition patterns from adolescence to young adulthood; timing and sequence of multiple life transition event (i.e., college graduation, full-time employment, marriage, and parenthood), and (2) the influence of transition patterns on the continuity and change of general psychopathology from adolescence to young adulthood. The present studies used a sample of 14,503 adolescents and their mothers from the National Longitudinal Study of Adolescent Health (Addhealth). The two studies used several types of person-centered analytical approaches to identify unobserved sub-populations of life transition patterns and longitudinal factor structures of psychopathology from adolescence to young adulthood. The findings suggest that early risk factors serve as a long-term stressor to create disrupted life transition patterns which are linked to vulnerable transition or change patterns of psychopathology from adolescence to young adulthood. The results also showed that on-time transition experiences during transition period to young adulthood redirected their transition patterns of psychopathology to less vulnerable group in adulthood. These
results highlights the needs of prevention and intervention program for selective target youths in both adolescence and transition time period.

INDEX WORDS: Life transition patterns, Early contextual and individual risk factors, General psychopathology, and Developmental patterns
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DEDICATION

This is dedicated to my wife who always pushed me to do my best. I am so thankful to have had such a strong and loving my wife supporting me along the way.
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CHAPTER 1. GENERAL INTRODUCTION

1.1 Introduction

Consideration of the diverse ways young people move from adolescence to adulthood is important because different pathways have potentially important implications for functioning and quality of life later in adulthood (Macmillan & Eliason, 2003; Shanahan, 2000). Studies of the transition to adulthood have described the changing character of this stage in the life course, finding that it has become more diverse, and individualized (Shanahan, 2000). More recently, Settersten (2007) suggested multiple transition patterns by ages 25-27 in terms of the “big 4” transition markers comprising educational attainment; work status, romantic partnership, and parenthood. It has been argued that individual differences in completing the four transition markers are greatest around age 25 and relatively small before age 20 and after age 30 (Cook & Furstenberg 2002). Despite evidence for greater variability in the timing and sequencing of transitions into adult roles and responsibilities, recent empirical investigations have identified a limited number of distinct transition pathways differentiated primarily by focusing only timing of single event such as timing of marriage (Osgood, Ruth, Eccles, Jacobs, & Barber, 2005). Given the multiple transition events, previous studies have limitations to fully understand life transition patterns regarding the timing and sequence simultaneously. Thus, comprehensive investigating multiple transition patterns provides important insights about life transition patterns to adulthood.

1.2 Dissertation Organization

Figure 1 depicts an overall theoretical model containing two main questions: (1) why life
transition patterns become more diverse, and individualized, and (2) how the individualized life transition patterns are associated with the continuity and change in psychopathology from adolescence to adulthood. In order to address these two questions, this dissertation contains two independent studies concerning multiple transition patterns. Given the importance of individualized life transition patterns, the first paper used a person-centered analytical approaches to identify heterogeneity (sub-populations) in life transition patterns using the four major transition markers and explored how individual characteristics and contextual adversity additively and multiplicatively influence multiple transition patterns. The second paper investigated the general factor of psychopathology in both adolescence and adulthood and then examined how the multiple transition patterns had moderating influences on the continuity and change in psychopathology from adolescence to adulthood. The detailed descriptions of each study are shown below.

--- Insert Figure 1 About Here ---

The main purpose of the first study was to investigate why life transition patterns become more individualized. In order to address this question, past studies have emphasized the unique roles of individual and socioeconomic or contextual characteristics on transition patterns. For example, Foster, Hagan and Brooks-Gunn (2008) emphasized the contextual effects on social attainments in adulthood. According to their suggestions, youths who grow up in economically deprived families (i.e., early contextual adversity) usually take on greater household and financial responsibilities, which hinder not only completion of high school but also continuation in college education (Upchurch, 1993). As a great deal of health research has revealed over the years, educational attainment has been, and remains, a core indicator of socioeconomic position through the life-course (Kawachi, Adler, & Dow, 2010; Wickram, O;Neil & Lee, 2015). Thus,
these disadvantaged youths with low levels of education attainment are commonly limited to attenuating employment as high earning full-time workers, which delays the timing of marriages and parenthood. In contrast, some studies have suggested the association between individual characteristics and social attainments in adulthood. For example, Damian and colleagues (2014) emphasized the importance of individual characteristics to predict education attainment and occupational prestige in adulthood, which may influence the timing of other transition events such as marriage and parenthood. They reported that personality traits compensate for contextual adversity and strongly influence education and income attainment in adulthood. These two different aspects provide meaningful ideas to investigate the unique effects of contextual and individual characteristics on the transition patterns to adulthood (additive effects).

Furthermore, many studies have suggested the role of personal characteristics on developmental outcomes under a specific environment (i.e., person × environment interactions; Mann, Kretsch, Tackett, Harden, & Tucker-Drob, 2015). This framework allows researchers to investigate how individual characteristics influence developmental outcomes under a certain specific environment (i.e., multiplicative or interaction effect). Linked to the first study, the framework leads to investigate the multiplicative effects between individual and contextual characteristics on transition patterns. Taking into account all previous aspects, the goal of the first paper is to understand how early contextual adversity and individual characteristics additively and multiplicatively influence the pathways of divergent transition patterns.

The second paper developed in the first paper by examining developmental continuity and discontinuity of psychopathology consisting of internalizing problems (i.e., depressive symptoms), externalizing symptoms (i.e., delinquency), and substance use (i.e., smoking) from adolescence to young adulthood and the moderating roles of multiple life transition patterns. Past
psychopathology literatures commonly have included substance use as one of indicators of externalizing symptoms in adulthood (Krueger, 1999). However, Verona and colleague (2011) reported the importance of substance use as a unique dimensionality to understand youth psychopathology. Given co-occurring all three domains, these three specific domains may exist as a longitudinal latent construct of general psychopathology in adolescence. For example, Measelle, Stices, and Hoganses (2006) demonstrated a longitudinal higher-order factor structure using depressive symptoms, eating, antisocial and substance use problems using a female adolescent sample.

Furthermore, recent developmental studies have begun to examine dynamic patterns of internalizing (such as depressive symptoms and anxiety) and externalizing problems (antisocial behaviors) from adolescence to young adulthood (Olino, Klein, Lewinsohn, Rohde, & Seeley, 2008). However, given the existence of general psychopathology, less is known about heterogeneity in hierarchical structure of psychopathology in a longitudinal context. More importantly, past developmental studies have emphasized the developmental continuity of psychopathology. However, Rutter (2013) suggested that there are several sorts of psychopathology wherein there is possibility for both continuities and discontinuities. Thus, previous studies have not fully taken into account both developmental continuity and discontinuity of psychopathology. In order to estimate these dynamic patterns of psychopathology, the transition period between adolescence and young adulthood may be necessary to be treat this transition period as a period of developmental discontinuity of psychopathology, and investigate both developmental continuity and discontinuity simultaneously. The main purpose of second study examined this transition mechanism of psychopathology from adolescence to adulthood. Related to the life transition patterns which is
the key variable of the first study, the transition patterns of psychopathology between adolescence and adulthood may be more dynamically changed, because the many transition events (entering college, full-time employment, marriage, and parenthood) occurs during this time period. In this regard, I expect that the non-conventional life transition patterns (i.e., off-time events) may amplify developmental patterns of psychopathology contemporaneously, which implies the moderating roles of transition patterns on the development of psychopathology (O’Rand & Hamil-Luker, 2005). In contrast, youths may positively re-direct their psychopathology if they experience positive transition events such as completion of a college degree which leads to follow more conventional transition patterns (transition from full time schooling to work and then to marriage, and childbearing). Analogous mechanisms of non-normative life transition patterns, this conventional transition patterns may help recover from high levels of psychopathology (i.e., buffering effect), which implies the moderating role of life transition patterns on developmental discontinuity of psychopathology during transition period to adulthood. Thus, the purpose of the second paper is to examine transition patterns of psychopathology from adolescence to young adulthood and then investigate how life transition patterns can moderate transition patterns of psychopathology from adolescence to young adulthood.
CHAPTER 2. STUDY 1
The Influence of Socioeconomic Context and Individual Characteristics on the Life Transition Patterns from Adolescence to Young Adulthood:
A Multivariate Discrete-Time Survival Mixture (MDTSM) Modeling

2.1 Introduction

Life course research has been guided by the notion that an individual’s development involves the timing and sequence of multiple social roles over time (Elder, 1985; Martin, Blozis, Boeninger, Masarik, & Conger, 2014). For many decades, past literature suggested that four transition markers delineated entry into adulthood: completing school, beginning one’s career, marrying, and becoming a parent (Shanahan, Porfeli, Mortimer, & Erickson, 2005). The social timetable theories emphasize the importance of considering the timing of events and the sequence of event occurrence (Elder, 1975). That is, social norms exist regarding the approximate age and sequence of events for when social roles, activities, or life events are expected to occur (Neugarten, 1979). Those who experience an event, such as getting married, at the normative (or typical) time their peers experience that event would be said to be on-time; those who experience events earlier or later than the norm would be off-time. Atypical timing and sequencing of experiences may be associated with adverse outcomes or problems in adjustment for a number of reasons (Rook, Catalano, & Dooley, 1989). When events are off-time, negative social sanctions may be imposed for deviating from the normative pattern (Elder, 1975). Such individuals may also have fewer social resources than individuals experiencing on-time events because fewer of their peers are experiencing the same events (Neugarten, 1979).
Thus, individuals who have difficulties in adjustment may be more likely to deviate from social norms, either intentionally or unintentionally. For these reasons, many researchers typically have focused on the timing of each transition event, such as the timing of an individual’s first child or first employment, and they typically examine this event in isolation from other life course events using conventional methods, such as logit model or univariate survival model. Given that youths experience multiple transition events from adolescence to young adulthood, dissecting the life course in such a way limits our understanding of the life course as a dynamic phenomenon (Macmillan & Eliason, 2003).

Regarding the timing and sequence of multiple transition events, more recent life course research has suggested that the pathways to adulthood are characterized by increased heterogeneity in transition patterns as many adolescents choose their own pathways to young adulthood in transitioning to young adulthood (i.e., de-standardization, McMunn et al., 2015; Ross, Schoon, Martin, & Sacker, 2009; Schulenberg, & Schoon, 2012). This suggestion implies that the timing of each transition event influences the sequence of other transition events. For example, early marriage or parenthood may hinder not only completion of post-secondary school but may also increase the probability of early employment. Consistent with this idea, using a sample in the United Kingdom (with an average sample age of 26), Ross et al. (2009) identified two distinct patterns, including the “conventional family” (limited college, full-time employed, married or cohabiting, and with children) and “work orientation without children” (college graduate, full-time employed, married or cohabiting, and with no children). Also, Schulenberg and Schoon (2012) identified a third pattern of “slow starters” (those with medium to low levels of education, who were single with no children, employed, and living with their parents) along
with the two more common structures (i.e., conventional family and work orientation without children).

While these previous studies provide valuable insights regarding the sequence of multiple transition events in young adulthood, most researchers typically focus on one or two aspects of transition events, such as school-to-work transition; then they examine these transition patterns in isolation from other life course events. However, the timing and sequence patterns of life events may be more heterogeneous. Furthermore, conventional methods, such as linear and logit regression, or univariate event history models have been commonly used to estimate the timing of separated, single events. These methods are limited, in that, they ignore the timing and sequencing of multiple transitional life events together over time. According to Arnett (2007), the years from the late teens through the 20s are when the transition to adulthood takes place for most people. Thus, by age 30, most people in Western societies have settled into their adult roles, which include a stable work context, marriage, and parenthood. However, given the importance of the timing and sequencing for multiple transition events, there can be a number of plausible combinations for the sequence of transition events from age 18 to 30. The life course pathways are not expected to be the only pathways through the life course, but they provide a hint at the underlying multiple patterns (i.e., unobserved heterogeneity in transition patterns). Given the existence of multiple plausible transition patterns, an explanatory analytical approach is needed rather than a confirmatory analytical approach. Thus, the current study do not formulate hypotheses with regard to the sequences of transition events. Instead, the study takes an exploratory approach (rather than confirmatory approach) to identify unobserved sub-groups who have experienced different transition events sequences (i.e., a person-centered typological approach). Thus, the first purpose of present study extends previous studies by systematically
investigating unobserved heterogeneity in the timing and sequencing of multiple life transition events occurrence (using four transition markers) during the transition period from adolescence to young adulthood (aged 18 to 30) using multivariate discrete-time survival mixture modeling.

Second, the purpose of the current study is to investigate how early contextual characteristics (cumulative socio-economic adversities) and individual psychosocial characteristics (i.e., future orientation, impulsivity, depressive symptoms, problem behaviors, and deviant peer affiliation exposure) addictively and multiplicatively influence the timing and sequencing of multiple transition events (i.e., transition patterns to adulthood).

**Early Cumulative Socioeconomic Adversity and Life Transition Events**

Previous developmental studies have suggested that exposure to multiple risk factors early in life has more adverse developmental impacts than singular risk exposures (Evans, Li, & Whipple, 2013; Schoon et al., 2002), suggesting that the higher one’s cumulative risk score, the more likely he or she is to encounter maladaptive outcomes (i.e., additive effect). Therefore, cumulative socioeconomic disadvantage has more long-term effects on individual development than single adversities (Ackerman, Schoof, Levinson, Youngstrom, & Izard, 1999; Evans et al., 2013). Consistent with this suggestion, Cicchetti and Tucher (1994) reported that early adversities may be overcome by improved circumstances, but may, nevertheless, leave the individual potentially more vulnerable to any disadvantage experienced at a later stage. More recently, using longitudinal data sets, Evans and Kim (2012) also replicated the longitudinal relationship between early cumulative adversity and health outcomes in adulthood. They suggested that early cumulative socio-economic disadvantage has an immediate impact (i.e., proximal effects), but vulnerabilities may emerge later in life (i.e., distal effects). Taking into account previous findings, early cumulative socio-economic disadvantages may serves as
chronic and proliferating stressors and have unique long-term effects on individual development.

Given the long-term persistent effects of cumulative adversity on developmental maladaptive outcomes, early cumulative socio-economic adversity may also directly influence the timing and sequence of transition events. For example, Wickrama, O’Neal, and Oshri (2014) demonstrated that early cumulative socioeconomic adversity directly affects the likelihood of experiencing a precocious transition to adulthood (‘rushed to adulthood’), which may place youths at risk for deviating from the normative transition patterns (Elder, 1975). Taking into account that youth who experience cumulative adversities are more vulnerable compared to those who experience a singular adversity, youths from multiple disadvantaged circumstances may be less likely to form normative networks with social institutions (such as schools, churches, or community organizations) because of their lower levels of social skills and reduced social acceptance. Thus, they may lack opportunities to learn social norms regarding “on-time” event occurrence (Neugarten, 1979). Consequently, they may not follow conventional patterns to adulthood. Rather, they may be more likely to take on early adult roles or delay their adult roles.

Furthermore, early cumulative adversities influence the sequence of transition events. For example, previous studies reported that early cumulative adversities put adolescents at risk for low education attainment in adulthood (Horan & Widom, 2014), which is one of “main keys” that influences the occurrence of other transition events (Hogan & Astone, 1986). Also, Amato and colleagues (2008) demonstrated that early adversities (i.e., low parental education, family disruption, and single parenthood) significantly influence the marriage-to-parenthood transition, which may disrupt individuals’ educational attainment. Similarly, early or teenage parenthood, which has been shown to be influenced by cumulative adversity, may initiate the sequential occurrence of other transition events, such as early excessive working and dropping out of...
school. Given these findings from previous studies, the current study hypothesizes that early cumulative adversities influence heterogeneity in the timing, as well as the sequence, of transition events in adulthood.

**Early Individual Characteristics and Transition Events**

**Future orientation**

Individual psychosocial and behavioral characteristics may also influence the timing and sequences of transition events have been suggested. Developmental research has increasingly focused on youths’ future orientation as an important psychological resource (i.e., a resilience or protective factor) that can influence transition events (Beal & Crockett, 2010). Evidence suggests that expectation of the future can motivate current behavior and future outcomes (Greene & DeBacker, 2004). Identifying positive future goals serves numerous functions in terms of self-enhancement and motivation. Furthermore, recognition of future orientation can motivate individuals to reduce discrepancies between their current situations and their desired future selves (Strahan & Wilson, 2006). In order words, being able to picture an improved “future me” can make me feel better in the moment while also incentivizing behavior designed to achieve that “future me” and discouraging behavior that might hamper un-desired outcomes (Clinkinbeard, 2014). This individual attribute is particularly pertinent for individuals during times of developmental transitions because it helps them prepare for the future. Thus, future orientation is highly relevant to the period of adolescence (Seginer, 2008). Future orientation may lead youth to experience transition events at the normative (or typical) time by successfully completing their developmental tasks ‘on-time’. Thus, the current study anticipates that youths who have higher levels of future orientation may more likely to follow a conventional sequence
of transition events (i.e., first graduate college, then gain full-time employment, then marry, and then have children).

**Personality trait (Impulsivity)**

Personality traits in adolescence may serve as another unique characteristic to predict the timing and sequence of adolescents’ transition events (Damian, Shanahan, Trautwein, & Roberts, 2014). In the present study, I focus on impulsivity as the most relevant personality trait in relation to transition events. Impulsivity has been defined as the tendency to act on behavior impulses without planning or without considering potential consequences (Harden & Tucker-Drob, 2011). According to the dual system model (Casey, Getz, & Galvan, 2008; Steinberg, 2008), adolescent behavior is formed by a developmental imbalance between two neurobiological systems: socioemotional system (which is responsive to emotion, novelty, and reward) and cognitive control system (which is critical for impulse control [inhibit control], emotion regulation, and decision making). During the adolescent developmental period the socioemotional system appears to become more sensitive, whereas the cognitive control system is usually less sensitive (Casey, Galvan, & Hare, 2005; Galvan et al., 2006). Thus, most youth are likely to be impulsive to some extent. However, Carroll and colleagues (2006) reported that high levels of impulsivity are associated with impaired cognitive control. Thus, impulsive adolescents may experience an increased responsiveness to immediate rewards, affective cues, and novelty (i.e., sensation seeking), while still having immature capacities for impulse control and inhibition for delayed gratification. These impulsive youth may act more on immediate rewards or novelty, which may not be lead to a conventional sequence of transition events.

Previous studies noted a negative relationship between impulsivity and future orientation (Oyserman & Saltz, 1993). However, future orientation is a broader construct that involves
cognition (future planning, anticipating, exploring and making decisions about future opportunities), motivation (goals, interests, values, commitments about the future, and concerns, doubts, and fears), and effective dimensions (evaluative emotions and attitudes such as feelings of optimism, pessimism, hopefulness, and despair; Nurmi, 2005), whereas impulsivity largely involves emotional and control neurobiological dimensions (dual system model; Harden & Tucker-Drob, 2011). Thus, individuals with impulsivity focus more on immediate gratification (Chen & Vazsonyi, 2011). The current study posits both future orientation and impulsivity may uniquely influence the timing and sequence of transition events. For instance, given suggestions from previous findings, I anticipate that youths who have high levels of impulsivity are more likely to experience certain transition events that may provide instant rewards such as early sexual behavior, which may result in early pregnancy or parenthood, earlier than other youth. In these instances, the “early” off-time event may then predict a sequence of other early transition events.

**Depressive symptoms**

Previous life course studies suggest that depressive symptoms in adolescence are significantly associated with the timing of transition events. For example, depressed individuals are less likely to receive social support compared to non-depressed persons (Miech, Caspi, Moffitt, Wright, & Silva., 1999). Therefore, youths who have high levels of depressive symptoms may marry to avoid social isolation (Carlson, 2012). Early marriage is highly connected to early childbearing (parenthood), which often hinders the completion of post-secondary school (Oesterle, Hawkins, Hill, & Bailey, 2010) and leads youths to join the work force prematurely. On the other hand, lower levels of life satisfaction among depressed youth may lead to their lack of interest in effectively navigating the pathway to adulthood, which may
delay the occurrence of transition events, such as college graduation and full-time work (Lewinsohn, Rohde, Seeley, Klein, & Gotlib, 2003). Consequently, transition events may be less likely to occur for depressed youths. Consistent with this notion, previous life course research has reported a longitudinal association between levels of depressive symptoms and off-time marriages (earlier and later than typical ages; Calson, 2012). Thus, I anticipate that depressive symptoms in adolescence uniquely influence the timing and sequence of transition events in adulthood.

**Problem behavior**

Delinquency or problem behavior in adolescence has been linked to a precocious transition to adult roles, including early sexual behavior, teenage parenthood, and school dropout, as well as problems with the assumption of adult roles (Oesterle, et al., 2010) and less socioeconomic success, such as unemployment and less education attainment (Newcomb & Bentler, 1988). However, another potential mechanisms may exist on the association between problem behavior and transition events. Given Moffitt’s adolescence-limited offender perspective (1993), some adolescents temporarily engage in antisocial behavior (minor forms of delinquency) due to the gap between biological maturity and social maturity (maturity gap; Barnes & Beaver, 2010). Therefore, as youths gain social maturity in young adulthood, problem behaviors are thought to decrease. However, decreased problem behaviors may not lead all youths to experience “on-time” transition events because they may not prepare well for adult roles in adolescence. Thus, they may extend a period of exploration for adult roles, which hinder to advance in their progression into adult roles. For this reason, they may not experience most of transition events in a timely manner. Taking into account these perspectives, I anticipate that delinquency will also predict the timing and sequence of transition events.
Deviant peer affiliation

Also, adolescents take more risks when they are with peers than when they are alone (Silva, Shulman, Chein, & Steinberg, 2015). Concerning their individual characteristics, research demonstrated that peers tend to resemble each other (i.e., homophily effect; Reitz, Zimmermann, Hutteman, Specht, & Neyer, 2014). Therefore, role expectations that are reflected in peer norms uniquely influence individual attributes (i.e., peer-group influence; Epstein, Bang, & Botvin, 2007, Reitz et al., 2014). According to Moffitt’s (1993) taxonomic theory, antisocial friends are increasingly accepted during adolescence because their delinquent behavior emerges as a desirable social resource (Rulison, Kreager, & Osgood, 2014). Then, peer susceptibility to deviant peer influence is greatly reduced by age 20, which includes the transition period to adulthood (Monahan, Steinberg, and Cauffman, 2009). In line with the process of peer-group influence and previous findings, youths who have deviant peers may be more likely to accept peer group norms, which may place youths at risk during the transition period to adulthood compared to those who have no deviant peers.

Multiplicative Influence of Socioeconomic Adversity and Individual Characteristics (i.e., Interaction Effects)

The developmental system perspective on human development (Lerner, 2004) emphasizes plasticity, or the potential for systematic within-person change across the life course. A major source of plasticity lies in interactions between individuals and their contexts (Galambos & Krahn, 2008). That is, explanatory mechanisms for inter-individual change include individual attributes in interaction with contextual conditions. Because relations between individuals and contexts are aspects of a dynamic system, it is crucial to observe individuals over time to capture how the individual-context relations influences development (Lerner, 2004). A
number of longitudinal studies have examined the questions of whether early individual characteristics alter the nature of the relations between early cumulative adversity and various developmental consequences (such as cognitive development, and psychopathology) in later life (Evans et al., 2013). This implies that early individual characteristics (future orientation, impulsivity, depressive symptoms, problem behavior, and deviant peer affiliation) may influence the association between early cumulative socio-economic adversity and transition patterns to adulthood.

From the stress-process model (Pearlin, Menaghan, Lieberman, & Mullan, 1981), negative individual characteristics (i.e., low levels of future orientation and high levels of impulsivity, psychopathology, and exposure of deviant peers) may make an individual more vulnerable to negative consequence in response to stressful socioeconomic environments (i.e., high levels of early cumulative adversity). In line with this perspective, existing resilience literature also reported that negative individual characteristics (e.g., depressive symptoms) reduce resilience through undesired coping skills (e.g., the use of avoidance or withdrawal) in response to stress or adversity (Compas & Reeslund, 2009). Therefore, internalizing symptoms (e.g., depressive symptoms) and/or externalizing behavior (e.g., problem behavior) are thought to increase the susceptibility of youths to stressful environments (i.e., cumulative socio-economic adversity). Mastern and Tellegen (2012) contend that when high levels of adolescent adversity were accompanied by limited adaptive capacity (i.e., low levels of resilience), high stress reactivity (i.e., more vulnerable to negative environments) was observed in young adulthood. This vulnerability or increasing stress reactivity may influence the timing and sequence of transition events. That is, individual characteristics may moderate the association between early adversities and transition patterns (i.e., timing and sequence of transition events). Taking into
account this interaction perspective, it is crucial to understand how each individual characteristic uniquely and/or jointly influences both the timing and sequence of multiple transition events. Thus, the current study investigates the role of five individual characteristics (i.e., future orientation, impulsivity, depressive symptoms, problem behavior, and deviant peer affiliation) on the association between cumulative socio-economic adversity and the timing and sequence of multiple transition events. Given findings from previous research, I anticipate that individual characteristics change the negative effects of cumulative adversity on life transition patterns.

**Gender and Race/Ethnic Group Differences**

If the timing and sequence for multiple transition events are associated with gender, it is possible that the association between predictors and transition patterns may be spurious. More importantly, it is surprising that most life course studies have analyzed male and female separately (Mouw, 2005; Sandefur, Eggerling-Boeck, & Park, 2005), which provides an incomplete understanding of how men and women differ in their transitions to adulthood. Previous studies have suggested that men's and women's life courses still differ with respect to family formations, such as the timing of marriage and parenthood (Moen, 2001; Williams & Umberson, 2004). For example, men marry and have children later than women (Woodward, Fergusson, & Horwood, 2006; Oesterle et al., 2010), which may lead to gender discrepancies in the sequence of other transition events. Consistent with this notion, I anticipated that women experience earlier marriage and parenthood compared to men (Oesterle et al., 2010).

Not only is there a likely gender effect, but ethnic group differences can be another concern in examining the conditional effect of timing and sequence of multiple transition events. Previous findings suggested that for some racial/ethnic groups, early family formation (i.e., early marriage and parenthood) presents more of an impediment to subsequent educational attainment
than it does for others (Forste & Tienda, 1992). For example, African Americans are more likely to engage in early family formation behaviors than others (i.e., precocious development; Glick, Ruf, White, & Goldscheider, 2006), which may lead to delays in other transition events (e.g., college graduation).

Based on these findings, gender and ethnicity effect should be accounted for in order to estimate unbiased effects for the other contextual and individual characteristics predictors. Therefore, gender and ethnicity were investigated not only to estimate unbiased effects of other predictors, but also to estimate how gender and ethnicity differently influence transition patterns.

2.2 Specific Study Hypotheses

This study first empirically identifies heterogeneity of multiple transition patterns using four markers (completion of college degree, full-time employment, marriage, and parenthood) and then investigates how early context and individual characteristics additively and multiplicatively influence the timing and sequence of transition patterns. The current study used a structural equation modeling (SEM) framework to analyze data from a longitudinal sample of adolescents participating in the nationally representative National Longitudinal Study of Adolescent to Adult Health [Add Health]). Figure 2 depicts my specific hypotheses:

--- Insert Figure 2 About Here ---

**Hypothesis 1.** Heterogeneity exists in the life transition patterns that occur between the ages of 18 and 30.

**Hypothesis 2.** Early cumulative socio-economic adversity influences the heterogeneity of multiple life transition patterns.
Hypothesis 3. Early individual characteristics (i.e., future orientation, impulsivity, depressive symptoms, problem behavior, and deviant affiliation exposure) influence the heterogeneity of multiple life transition patterns.

Hypothesis 4. Individual characteristics moderate the association between early cumulative socio-economic adversity and life transition patterns.

Hypothesis 5. Transition patterns vary across gender and race/ethnicity groups.
2.3 Method and Measurements

Sample and Data

Data for this study were drawn from a nationally representative sample of adolescents participating in the National Longitudinal Study of Adolescent to Adult Health (Add Health). In 1995, baseline (Wave 1) data were derived from a complex cluster-sampling of middle and high school students, yielding 20,745 respondents 12–19 years of age (average age was 15.5 years), from 134 middle and high schools. To ensure diversity, the sample was stratified by region, urbanicity, school type (public vs. private), racial composition, and size. Second, third, and fourth wave data were collected in 1996, 2001, and 2008 (Wave 2 = 14,738 respondents, Wave 3 = 15,170 respondents, and Wave 4 = 15,701 respondents). The median education level of mothers and fathers was high school or GED completion. About 11% of the households received food stamps. More information about Add Health is available at http://www.cpc.unc.edu/projects/AddHealth. The final sample consisted of approximately 53% women, and 35% of respondents reported a minority racial/ethnic status with the largest percentages reported for African American (15.8%), Hispanic (13.2%), and Asian (6.0%) racial/ethnic minorities, respectively. Add Health incorporates sampling weights that account for the unequal probability of selection; for proper weighting when conducting time-to-event analyses, weights from the first wave are used, and individuals with missing weights must be removed (Chen & Chantala, 2014). After removing individuals with missing Wave I weight variables (8.8% of the sample), the present study uses data from 14,503 respondents who participated in Wave 1 (with no missing data on age, gender, or race/ethnicity) and provided transition event measures at Wave 4 (2008) when they were aged 25-30.
Measures

**Multiple transition events.** Four role status variables were examined: college graduation, full-time work, marriage, and parenthood (Settersten, 2007). For each age from 18–30, a binary variable was created for each status indicating whether the individual occupied the status for the first time (on-set timing) at that age (coded 1) or had not occupied the status by that age (coded 0). Once the individual occupied the role status, they no longer contributed data for the remaining ages for that status (coded as missing) (Muthén & Masyn, 2005). To account for the fact that a relatively small percentage of individuals occupied one of the roles before they were 18 years old, the binary variable for age 18 represented whether the individual occupied the status for the first time at age 18 or younger (0.0% of total youths experienced college graduation before age 18; 0.3% of total youths experienced first marriage before age 18; 7.0% of total youths experienced first-full time work before 18; 1.9% of total youths experienced parenthood before age 18).

The role status variables were taken from the Wave 4 Add Health interview. The year of the respondent’s first degree (associate’s degree or bachelor’s degree) after high school was used to determine the age at which the first post-high school degree was obtained. The age when the person first began full-time work (at least 35 hours a week) was directly measured in the Add Health interview. The year of the individual’s first marriage was used to find the age of the respondent when they first married. The date of birth of the respondent’s oldest child was used to determine the age at which the respondent first became a parent.

**General future orientation.** At Wave 1 (1995), general future orientations was measured by six items capturing different domains (see Chen & Vazsonyi, 2011 for a full description). Five of the six items assessed adolescents’ perception of the likelihood of a future
event including going to college, getting married by age 25, living to the age of 35, being killed by age 21 (reverse coded), and getting HIV or AIDS (reverse coded). Responses to these items were captured on a 5-point Likert type scale ranging from 1 (little or no chance) to 5 (very likely or almost certain). The remaining item asked adolescents to rate how much they wanted to go to college on a 5-point scale ranging from 1 (low) to 5 (high). Using a principal component analysis, Chen and Vazsonyi (2011) reported that the six items have a high degree of construct validity (with an eigenvalue over 1.0). On the basis of these findings, all six items were summed ($\alpha = .65$).

**Impulsivity.** At Wave 1 (1995), impulsivity was measured by four items from the in-home interview (Thompson, Ho, & Kingree, 2007; Vazsonyi, Cleveland, & Wiebe, 2006). Items asked respondents to indicate on a 5-point scale ranging from 1 (strongly agree) to 5 (strongly disagree) whether they agreed with four statements (i.e., “When you have a problem to solve, one of the first things you do is get as many facts about the problem as possible,” “When you are attempting to find a solution to a problem, you usually try to think of as many different ways to approach the problem as possible,” “When making decisions, you generally use a systematic method for judging and comparing alternatives,” and “After carrying out a solution to a problem, you usually try to analyze what went right and what went wrong.”). A scale score was computed by summing the responses of all four items ($\alpha = .73$). According to Chen & Vazsonyi, 2011, this scale is an appropriate measure of impulsivity, as the items assessed a lack of deliberate thinking or planning, an inability to delay gratification, an unwillingness to weigh different consequences of a decision or a behavior, and a “here and now” orientation.

**Depressive symptoms.** At Wave 1 (1995), eight items from the Center for Epidemiological Studies of Depression Scale (CES-D; Radloff, 1977) were used to assess
adolescent respondents’ distress feelings (e.g., “felt depressed and sad”) in the past week. Scale responses ranged from 0 = never or rarely to 3 = most of the time or all of the time. Positive affect items were reverse coded before summing all items. This resulted in an index of depressive symptoms ranging from 0 to 24. The scale had adequate internal reliability (α = .80).

**Problem behavior.** At Wave 1, problem behaviors were measured with 14 items assessing a broad range of norm-violating behaviors within the past 12 months, ranging from minor acts, such as dishonesty to parent about whereabouts, to more serious offenses, such as being in a serious fight or selling drugs (e.g., “In the past 12 months, how often did you lie to your parents or guardians about where you had been or who you were with?”; see Chen & Vazsonyi, 2011 for a full description). Responses were given on a 3-point scale ranging from 0 (never) to 3 (five or more times). The problem behavior scores were computed by summing the responses of the 14 items (α = .81).

**Deviant peer affiliation.** At Wave 1, youths were asked how many of their three closest friends smoked at least one cigarette each day, smoked marijuana at least one time each month, and drank alcohol at least one time each month. Participants were also asked how often they took part in a fight where his/her group of friends fought against another group of people in the past 12 months (Lee, 2011). On an ordinal scale, participants indicated whether they fought with their peers against other youth 0, 1–2, 3–4, or more than 5 times. These four variables (smoking, marijuana, alcohol, group violence) were standardized using z-scores and then summed to create an overall measure of deviant peer affiliation. The standardized Cronbach alpha for the composite measure was 0.64.

**Cumulative socioeconomic adversity.** A composite index for cumulative socioeconomic adversity was created by summing dichotomous indicators capturing different dimensions of
adversity (Brody et al. 2013; Wickrama, O’Neal, & Lee, 2013). These indicators included low parental education, high family economic hardship, low parental marital stability, and high community adversity. Except for marital stability (already a dichotomous measure), dichotomous indicators were created by mean splitting the following measures.

**Parental education.** The responding parent reported both parents’ highest level of education obtained at W1 (1995). Responses ranged from: 1 = never went to school to 10 = professional training beyond four-year college or university degree. Mothers’ and fathers’ educational levels were summed to create an index of parental education. For single-headed families (n = 79) with no available data from fathers, maternal education served as the indicator of parental education.

**Economic hardship.** Five dichotomous items (0 = no, 1 = yes) assessed whether any member of the household received the following social service benefits in the past month: social security, supplemental security income, aid to families with dependent children, food stamps, or housing subsidies at W1 (1995). Responses to these five items were summed to create an index of economic hardship with a range of 0-5.

**Parents’ marital stability.** A binary variable was used to differentiate parents who had been consistently married to their spouse (or in a marriage-like relationship) for at least 15 years (1) from other parents (0). Fifteen years was selected as the cut-off because the average age of respondents at Wave 1 was 15 years. Thus, for most respondents this variable represents their parents’ continuous marriage for the duration of the child’s life.

**Community adversity.** Community adversity was assessed by summing four indicators corresponding to census tract information from the 1990 U.S. Census. The indicators included (a) the proportion of families living in poverty, (b) the proportion of single-parent families, (c)
the proportion of adults employed in service occupations, and (d) the proportion of unemployed men (Upchurch, 1993).

**Covariates.**

**Race/ethnicity.** At Wave 1, adolescents reported their race/ethnicity. Dichotomous variables were then created to assess African American, Hispanic, Asian, and White racial/ethnic statuses. The dichotomous variables for each of the minority statuses were included as independent variables in the regression equation resulting in regression coefficients that can be interpreted with reference to Whites (reference group = Whites). For multi-racial respondents, only their first choice of race/ethnicity category was considered.

**Sex.** Sex was coded as man (0) or woman (1).

**Age.** The effect of multiple predictors on the timing and sequence of transition events may be associated with different age group at same time measurement (i.e., cross-sequential design; Little, 2013). Therefore, respondents’ age at wave 1 was used as a control variable. Participants’ age (mean age: 15.61, SD = 1.72) at Wave 1 was calculated by subtracting their birth date from the interview date.

**Analysis Plan**

**Discrete-time survival model.** One of the main purposes in the current study is to investigate the timing of transition events from adolescence to young adulthood (age 18 to 30). These transition events serve as a key influence on the sequence of other transition events occurrences. In order to investigate the timing of event occurrence, two key data analysis questions must be addressed: (1) how complete are the data on event occurrence and (2) how to define the unit of time?

**Censored data.** Connected to first question, it is essential to know the quantity of
interests – whether and, if so, when the target event occurs for the sample respondents. In order to take into account these two issues, it is important to be aware of the nature of censored data. Singer and Willett (2003) labeled people with unknown event times censored observations, which hinders understanding on whether and, if so, when the target event occurs for the sample. Allison (2010) described two major reasons for censored individuals: (1) an unknown time-point for the event occurrence due to dropout during the study period (i.e., right-censoring); and (2) an unknown time-point for the event occurrence because the target does not experience the event during the study period. The latter individuals are less problematic because those individuals can remain in the risk set (i.e., the set of individuals who did not experience the target event) and are considered representative of the study population (Singer & Willer, 2003). However, failure to take account for the former individuals (those who drop out during the study period) in the analyses may produce a serious bias in the model parameter estimations.

Previous studies have incorporated censored individuals in the analyses using two common approaches. The most common approach is to exclude all censored individuals from the analyses due to the unknown time points (Singer & Willett, 2003). However, to estimate the unbiased timing of event occurrences, data from both the censored and the uncensored cases must be incorporated simultaneously in the analysis. Even though those cases do not provide information on the timing of event occurrence, those censored cases still contain the history before they drop out, which is important for an accurate estimation of the risk set (i.e., individuals who did not experience the target events) at a specific time period. Second common approach is to estimate the timing of event occurrence at some particular point in the time. The second relatively common approach is concerned with whether the event has occurred by the time (Sargeant, Bruce, Florio, & Weissman, 1990). This is accomplished by dichotomizing all
participants and assigning a code of 0 to those for which the event does not occur and 1 to those for which the event occurs during the specific time points of interest. This approach answers the question regarding whether the event has occurred during the specific time period in a cumulative manner. However, this approach also has several problems. First, this imputed value for censored individuals may produce biased parameter estimates regarding the timing of events. Second, this imputed approach does not provide an answer to the when question. By dichotomizing all participants (0 [= no event occurrence] and 1 [= event occurrence]) during the time period, some participants remain in the risk set even though they experienced the event.

Muthén and Masyn (2005) suggested that either once the individual experienced the event or individuals dropout at specific time, they no longer contribute data to estimate the timing of event occurrence. For examining the timing of events, those censored individuals should be coded as missing, rather than coded as 0. In censored data, the conventional assumption of these missing cases is that censoring times are independent of event occurrence times (non-informative censoring assumption; Allison, 2010), corresponding to the assumption of ignorable missingness (Little & Rubin, 2002; Muthén & Maysn, 2005). Therefore, it is generally assumed that the missing cases in the censored date are ignorable; in the sense that, the reason for the individual dropping out during the study period is unrelated to the individual's event status following drop out. Therefore, the censored data should be taken into account simultaneously in order to investigate whether the event has occurred during specific time period (i.e., cumulative event incidence) and when the event occurred (i.e., instantaneous timing of event). Conventional linear models, such as a regression or logistic model, are limited in their ability to take into account both questions (i.e., whether and when questions).

**The scaling issue of time.** Another issue is connected to whether the time variable
measuring the state of the event is continuous or discrete. Continuous-time methods assume
event times can be measured exactly—thus there should be no “ties” in the dataset where two or
more people have the same event time. While it may be logical to think of time as a continuous
variable, this assumption is often unrealistic in practice. This is especially true for data collected
in the social and behavioral sciences, as researchers frequently ask for the year or age of an event
rather than the exact date. Also, events can sometimes only occur at discrete points in time (e.g.,
year before school-dropout). In addition, discrete-time methods can be used to approximate the
results of a continuous-time survival analysis (Vermunt, 1997) and are conceptually and
computationally simpler. For these reasons, the discrete time survival model is appropriate for
social science research (Muthén & Masyn, 2005).

Discrete-time survival model

*Three survival functions (\( \hat{h} \), \( \hat{S} \), and \( \hat{D} \)) of discrete-time survival model.* The main
purpose of the discrete-time survival analysis (also known as *event history analysis*) is to
appropriately handle both censored data and a discrete time scale (Singer & Willett, 2003).
Taking into account the censored individuals, the discrete survival model commonly uses three
probability functions: hazard probability, survival probability, and lifetime distribution
probability. First, a hazard probability (\( h \)) estimates the *instantaneous timing of event*. In the
model, the hazard probability function (\( h \)) is defined as:

\[
\text{Hazard probability (} h_{ij} \text{)} = P(T_i = j \mid T_i \geq j)
\]

Equation 1

where \( T \) is a random variable that indicates the time period when the event occurs, \( i \) is an
individual, and \( j \) is a time period. \( h_{ij} \) is the conditional probability that individual \( i \) experiences
the event \( T \) in time period \( j \) given that it was not experienced before time \( j \) (see equation 1). In
the dataset, the sample-estimated hazard probability (\( \hat{h} \)) can be estimated using the follow
equation (Singer & Willett, 2003):

$$\text{Sample-estimated hazard probability}(\hat{h}_j) = \frac{n \text{ Event}_j}{n \text{ at risk}_j} \quad \text{Equation 2}$$

where $n \text{ Event}_j$ represents the number of individuals who experience the target event in time period $j$ and $n \text{ at risk}_j$ represents the number of individual at risk (i.e., individuals who did not experience target event) from time period $j-1$ to $j$. Therefore, this probability function estimates the conditional probability that an individual will experience the event in time period $j$ given that he or she did not experience it at any time prior to $j$. This probability provides the instantaneous probability function of occurrence of the event, which allows the researchers to investigate the “when” question.

Another useful function is the survival function ($S$) which can be defined as the probability that an individual “survives” longer than $j$ and is denoted $S_{ij}$:

$$\text{Survival probability } (S_{ij}) = P(T_i > j) \quad \text{Equation 3}$$

This function describes how many individuals do not experience the event by a given time $j$, which is the opposite of the hazard probability. Using sample-estimated hazard functions (equation 2), the sample-estimated survival function ($\hat{S}$) can be estimated using the following equation (Singer & Willett, 2003):

$$\text{Sample-estimated survival probability}(\hat{S}_j) = \hat{S}_{j-1} (1 - \hat{h}_j) \quad \text{Equation 4}$$

For example, assuming the estimated hazard probability ($\hat{h}_j$) is .10 at time $j$ (using equation 2) and the estimated survival probability is .08 at time $j-1$, the survival probability at time $j$ can be estimated as follows:

$$\hat{S}_j = .08 (1-.10) = .072.$$
where .072 indicates that an estimated 7% of all individuals have not experienced the target event by time \( j \). Therefore, this survival probability provides the \textit{cumulative probability function} which allows the researchers to investigate the “whether” question. This survival function is important to estimate the median lifetime point: an estimate of the time period when the event has occurred for 50% of the population (Singer & Willett, 2003). Follow Miller (1981), the median survival time can be estimated as follows:

\[
\text{median survival time} = m + \left( \frac{\hat{S}_j - 0.50}{\hat{S}_j - \hat{S}_{(j+1)}} \right) (m + 1) - m \quad \text{Equation 5}
\]

where \( m \) represents the time interval when the sample survival probability is just above 50%, \( \hat{S}_j \) is the expected value of the sample survivor function in that interval, and \( \hat{S}_{(j+1)} \) represents the expected value for the following interval (when the survival probability is just below 50%). For example, assuming that six years is the time point just above 50% of survival probability and the expected survival probabilities are .5189 and .4877 for \( \hat{S}_6 \) and \( \hat{S}_7 \), respectively. The estimated median survival time point of this event will be:

\[
6 + \left[ \frac{.5189 - .5}{.5189 - .4877} \right] ((6 + 1) - 6) = 6.6
\]

These descriptive measures are important when there is censoring, as conventional descriptive statistics, such as sample mean, are not useful for describing the center of the distribution and defining each distribution (Singer & Willett, 2003). If the survival probability is estimated, the last function, lifetime distribution probability function (\( D \)) can be defined as the probability that an individual has experienced the event by time \( j \) (see equation 6):

\[
\text{Lifetime distribution probability} \ (D_{ij}) = P (T_i \leq j) = 1 - S_{ij} \quad \text{Equation 6}
\]
Sample-estimated lifetime distribution probability\( (\hat{D}_j) = 1 - \hat{S}_j \) \hspace{1cm} \text{Equation 7}

In a similar interpretation of the sample-estimated survival function, the sample-estimated lifetime distribution probability function \( (\hat{D}) \) can be interpreted as the estimated probability that individuals experience the target event by time \( j \). Hence, the lifetime distribution also allows the researchers to investigate the “whether” question.

Single-event discrete-time survival model. The next step of a survival model is to estimate how covariates influence a single event of the survival function. In order to answer this type of research question, the discrete-survival model has been widely used (Allison, 1999; Singer & Willett, 1993). The sample-estimated hazard probability, \( h_j \) is modeled by a logit link function. Thus, the unstructured model of discrete-survival model can be as follows:

\[
\log \left( \frac{\hat{h}_j}{1 - \hat{h}_j} \right) = \beta_j
\]

\hspace{1cm} \text{Equation 8}

\( \beta_j \) is the baseline hazard (i.e., intercept when there are no covariates) at a given specific time period \( j \). In order to convert logit regression coefficients to probability values, the equation below can be used.

\[
\hat{h}_j = \frac{1}{1 + e^{-\beta_j}}
\]

\hspace{1cm} \text{Equation 9}

In the same manner as conventional linear regression, multiple covariates can then be added to predict the unique effect of covariates on the hazard probability of each individual. Thus, all model parameters are estimated after taking into account censored respondents, which produces unbiased parameters.

**Multivariate Discrete-Time Survival Mixture (MDTSM) Model**
The single-event discrete time survival model provides meaningful information regarding the timing of the target event. However, given the importance of the sequence of multiple events, this analytical approach is limited in its ability to estimate the survival probability for multiple events simultaneously. Using a structural equation modeling (SEM) framework, Dean, Bauer, and Shanahan (2014) recently proposed that the single-event discrete-time survival model can be extended to a multiple-event discrete-time survival model by adding multiple events simultaneously. Following their suggestion, the current study estimated multiple-event discrete-time survival probabilities by adding four transition events (i.e., college graduation, full-time employment, marriage, and parenthood) simultaneously.

Person-centered approaches, such as latent class growth models (LCGMs) or growth mixture models (GMMs), have been widely used in order to examine unobserved heterogeneity within a larger population (Jung & Wickrama, 2008; Ram & Grimm, 2009). Given the possibility of heterogeneity in the hazard function, Muthén and Maysn (2005) proposed estimating a univariate (i.e., single-event) discrete-time survival mixture model, a combined model using the single-event discrete-time survival model, and a growth mixture model. This modeling approach allows researchers to investigate the heterogeneity in single-event discrete-time survival functions. However, this analytical approach not only is conceptually different in some ways from the purpose of the current study, but also does not incorporate multiple events in the analytical process, which is key for identifying the sequence of transition events.

In aiming to fully understand the timing and sequence of multiple transition events, the current study used a combination of a multivariate discrete-time survival model and a longitudinal latent class model (LLCM; also known as RMLCA [Repeated Measures Latent Class Analysis], Collins & Lanza, 2010), which proposed by Dean, Bauer, and Shanahan (2013).
The main advantages of this analysis are its ability to handle censored data (timing of events) and the ability to identify heterogeneity in the unobserved sequence of multiple life transition pathways by examining the latent classes that reveal pathways to adulthood, or patterns of the events over time (Shanahan, 2000). For a clear understanding of this combined model and parameter estimation, the model building process is described as follows.

**Model building process**

**Date structure.** The current study employed an accelerated design in which age, rather than wave, was the unit of time (Bollen & Curran, 2006; Duncan, Duncan, & Strycker, 2006). Table 1 shows an example data structure for a multivariate discrete-time survival mixture model. Each age variable is a binary variable only containing 0 and 1. For each age from 18–30, a binary variable for each status was created indicating whether the individual occupied the status for the first time at that age (coded 1) or had not occupied the status by that age (coded 0). Once the individual occupied one of the role statuses, they no longer contributed data for the remaining ages for that status (coded as missing). For example, individual ID #1 did not experience any of four target events from age 18 to 30. ID #2 experienced all events simultaneously at age 19, and ID #3 dropped out after age 19.

--- Insert Table 1 About Here ---

*Estimate multivariate discrete-time survival mixture model (MDTSM).* The current study used a multivariate discrete-time survival mixture model, which combines a multivariate discrete-time survival model with a longitudinal latent class model. The four-step approach to conducting a conditional MDTSM analysis is described below.

*Step 1: Specify an unconditional multivariate discrete-time survival model.* The current study extends the univariate discrete-time survival model by adding multiple events
simultaneously. The sample-estimated hazard functions \( \hat{h} \) of each event can be estimated using a multivariate discrete-time survival model in a SEM framework. Using the null model (i.e., the model without any covariates), the descriptive statistics (such as sample-estimated hazard, survival, and lifetime distribution probabilities) of a discrete-time survival model can be estimated. First, the sample-estimated hazard probability \( \hat{h} \) can be estimated using equation 2. Once this probability is estimated, the other two survival probabilities (i.e., survival and lifetime distribution functions) can be easily calculated using equations 4 and 7. Also, the median survival time point can be calculated using equation 5.

**Step 2: Specify an unconditional longitudinal latent class model (LLCM).** Similar to the estimation of other longitudinal class models, several types of trajectories (e.g., linear, quadratic, or piecewise) can be directly specified into the discrete-time survival model to estimate distinct trajectories of hazard probabilities (see panel a of figure 3; Dean, Bauer, & Shanahan, 2013). However, specifying such trajectories are not essential for estimating all longitudinal class models. Consistent with this notion, Feldman, Masyn, and Conger (2009) proposed a longitudinal latent class model (LLCM) as an alternative approach, which is a type of mixture model, but it does not belong to the family of growth models. That is, the model does not estimate the trajectory (see panel b of figure 3). Instead, given the categorical (i.e., binary) class indicators, an LLCM estimates distinct response patterns (i.e., the items’ probability patterns) of repeated items (Collins & Lanza, 2010; Fish & Pasley, 2015).

--- Insert Figure 3 About Here ---

The current study used four different transition events, which contain the dynamic changes of the timing and sequence of transition events. Thus, imposing one simple time function of hazard (i.e., trajectory) across all transition events may produce biased estimations of
growth parameters. More importantly, LLCM estimates fewer model parameters than other longitudinal class models (LCGM and GMM) because the model does not contain growth parameters. Given the repeated measuring of multiple hazard probabilities from ages 18 to 30, the current longitudinal class model contains many class indicators (i.e., binary variables), which may lead to convergence problems when estimating the latent classes. Given the number of class indicators, LLCM performs better than GMM if the trajectory cannot be characterized as a simple hazard function (Feldman et al., 2009). Taking into account these two issues, the current study did not specify trajectories across all transition events. The multivariate discrete-time survival mixture model (MDTSM) is shown in figure 3, which is a combined model consisting of a multivariate discrete-time survival model and a longitudinal latent class model (LLCM).

--- Insert Figure 3 About Here ---

**Step 3: Class enumeration and model evaluation.** Like the normal procedure of estimating a latent class model, the next step is to select the number of classes and perform the model evaluation (i.e., optimal class selection procedure). Followed by instruction from Jung and Wickrama (2008), the current study utilized log-likelihood values (LL; higher values are preferred), sample size adjusted Bayesian information criterion (SSABIC; lower values are preferred), Akaike Information Criteria (AIC; lower values are preferred), Lo-Mendell-Rubin Likelihood Ratio Test (LMR-LRT; significant p-values are preferred), entropy of each class for indicating class separation (greater than .70 is acceptable [Muthén, 2000], class sizes (a minimum of 5% for the smallest group; Andruff, Carraro, Thompson, & Gaudreau, 2009), and an assessment of the interpretability of identified classes (Nylund, Asparouhov, & Muthén, 2007). To ensure a global maximum likelihood solution, at least 1,000 random sets of starting
values were used for each model, with the best 50 retained for final optimization. The resulting solutions were monitored to ensure that the final log-likelihood was replicated.

**Step 4: Adding covariates.** As shown in figure 4, several sub-groups of life transition pathways, several early contexts, individual characteristics, and their interaction terms (see the statistical model in figure 3) were systematically included in order to investigate additive and multiplicative effects of predictors on heterogeneity in life transition pathways (the timing and sequence of transition events) using a multinominal logistic model. The primary analyses followed a hierarchical multiple regressions approach. In order to estimate the unique main effects and to compare effect sizes among predictors, a contextual predictor (cumulative socioeconomic adversity) was entered in step 1, then five individual predictors (general future orientation, impulsivity, depressive symptoms, problem behavior, and deviant peer affiliation) were entered in step 2. The control variables, gender, race/ethnicity, and age, were entered in step 3. Interactions between the contextual predictor and each individual characteristics were then included in step 4. Each interaction was examined in a separate analysis to avoid multicollinearity problems (Aiken & West, 1991).

--- Insert Figure 4 About Here ---

In order to investigate the effect size of each model, the $R^2$ (known as explained variance) has been widely used (Coxe, West, & Aiken, 2013). However, given the nature of categorical outcomes, the $R^2$ cannot be directly applied to a multinominal logistic model. Instead, the current study used the pseudo-$R^2$ proposed by McKelvey and Zavoina (1975). According to their formula, the $R^2$ statistic refers to the explained variance proportion in an underlying continuous latent outcome variable (known as the latent response variable) (DeMaris, 2002; McKelvey & Zavoina, 1975). The formula for this measure is:
Pseudo- $R^2 = \frac{\text{Var}(\hat{Y}^*)}{\text{Var}(Y^*)} = \frac{\text{Var}(\hat{Y}^*)}{\text{Var}(Y^*) + \text{Var}(e)}$ \hspace{1cm} \text{Equation 10}

where $\text{Var}(Y^*)$ is the estimated variance of the latent outcome variable (i.e., latent response variable), $\text{Var}(\hat{Y}^*)$ is the variance of the predicted latent outcome variable, $\text{Var}(e)$ is the residual error variance of the latent outcome variable, which is fixed to $\pi^2/3$ for the logistic model. Simulation studies have shown this pseudo-$R^2$ is close to the $R^2$ for a linear regression (Coxe, West, & Aiken, 2013; DeMaris, 2002).

All predictors were mean-centered not only to prevent collinearity issues (Aiken & West, 1991), but also to represent the effects of each predictor at the mean level of the other, which provides a more meaningful interpretation (Aiken & West, 1991; Jaccard, Turrisi, & Wan, 1990). To interpret significant interactions, the simple slope for each moderator was computed at high and low levels of moderators (1 SD above and below the moderator mean; coded as 0 for “low”/below the mean and 1 for “high”/above the mean) (Aiken & West, 1991; Bauer & Curran, 2005).

As can be seen in figure 1, the purpose of the interaction effects was to investigate how individual characteristics influence the association between a contextual factor and transition patterns. Thus, cumulative socioeconomic adversity was used as the focal predictor, and the five individual characteristics were conceptualized as the moderators.

Furthermore, in order to determine the shape of the interaction effect, Aiken and West (1991) proposed the crossover point test. This test provides the observed point of a focal predictor where regression lines cross each other. For example, using mean-centered predictors, a linear regression with an interaction effect can be written as:

$$\hat{Y} = B_0^* + B_1^* X_1^* + B_2^* X_2^* + B_3^* (X_1^* \times X_2^*)$$ \hspace{1cm} \text{Equation 11}
where $X_1^*$ is a sample-mean-centered focal predictor and $X_2^*$ is a sample-mean-centered moderator; asterisks on $B_0^*$ through $B_3^*$ indicate regression weights for mean-centered variables. According to Aiken and West (1991), the crossover point can be estimated using the following equation:

$$\text{Crossover point} = -\frac{B_2^*}{B_3^*} + \bar{X}_1$$  

Equation 12

where $\bar{X}_1$ is the mean of the focal predictor. If the crossover point is contained in the range of values on $X_1$, regression lines cross each other (i.e., dis-ordinal interaction; Widaman et al., 2012). If the crossover point is outside the range of $X_1$, regression lines do not cross each other (i.e., ordinal interaction; Widaman et al., 2012). More recently, Widaman and colleague (2012) developed the re-parameterized regression model using an iterative fitting process to estimate the crossover point as well as its’ standard error with a confidence interval, which produces a more robust estimation of the crossover point. The current study used the re-parameterized regression model to investigate the crossover point. Furthermore, the current study tested simple slopes at specific points of $X_1$ to estimate the effect size of the focal predictor at that point (i.e., pick-a-point approach; Hayes & Matthes, 2009).

The use of these analytical procedures takes into account the clustered nature of the data and provides appropriate standard error estimates. All analyses will be performed using the Mplus 7.11 statistical software. In order to handle missing cases, including drop-outs in the current sample, all analyses were performed under FIML estimation (i.e., maximum likelihood estimation with robust standard errors [MLR]). The current study used the TYPE=COMPLEX analysis syntax in order to adjust for potential bias in standard errors and chi-square computation.
due to the lack of individual independence between observations within schools in the Add Health data.
2.4 Results

Sample-estimated hazard and lifetime distribution probabilities ($\hat{h}$ and $\hat{D}$) of population

The sample-estimated hazard probabilities for each event process are listed in Table 2 and displayed in Figure 5 (panel a). The sample observed lifetime distribution function for each event process is also displayed in Figure 5 (panel b).

--- Insert Table 2 and Figure 5 About Here ---

In general, the risk (i.e., timing) of full-time work was the highest in early ages (from ages 18 to 22) and decreased until age 30. For example, the risk of full-time work was the highest at age 18 ($\hat{h}_{age18} = .39$), but quickly decreased by age 20 ($\hat{h}_{age20} = .15$). However, the risk increased again by age 22 ($\hat{h}_{age22} = .34$) and then gradually decreased until age 30 ($\hat{h}_{age30} = .04$). The median age of full-time work was between 18 and 19. Also, the lifetime distribution probability was .88 by age 24, indicating that approximately 88% of youths experienced full-time employment by age 24. While the risk of beginning full-time work showed the clear pattern of timing (i.e., the highest in early ages and consistently decreased until age 30), the risk of other transition events (i.e., college graduation and family formation [i.e., marriage and parenthood]) was consistent and low in early twenties, but changed in mid- and late-twenties. For example, the risk of college graduation was relatively stable and flat until age 30 with only a small increase between age 22 and 23 ($\hat{h}_{age22} = .10$, and $\hat{h}_{age23} = .11$ [peck age]). The median age of college graduation was more than age 30 with a .43 of lifetime distribution probability by age 30, indicating that 43% of youths graduated college by age 30. In a similar manner, the risk of experiencing two family formation events (i.e., marriage and parenthood) was consistently low until age 30. For example, the risk of marriage was the highest [peck] from age 22 to age 26, but
the probability was small ($\hat{h}_{\text{age}22-26} = .07$). The median age of marriage was between 29 and 30 with a .52 lifetime distribution probability (i.e., cumulative hazard probability) by age 30. The risk of parenthood was the highest at age 18 ($\hat{h}_{\text{age}18} = .07$), but relatively stable until age 27 ($\hat{h}_{\text{age}27} = .06$). This risk decreased slightly by age 30 ($\hat{h}_{\text{age}30} = .04$). Like marriage, the median age of parenthood was also between age 29 and 30 with a .51 lifetime distribution probability by age 30.

Overall, the sample-estimated hazard and lifetime distribution probabilities indicated that full-time work rapidly increased from late adolescence to early twenties (from ages 18 to 24) while family formation (i.e., marriage and parenthood) was consistently low and stable in early twenties, but slightly change in mid- and late-twenties (from ages 24 to 30). The “risk” of college graduation only increases during early twenties (age 21 through 24). The differential timing of each transition event occurrence implies the existence of the sequence of transition events from adolescence to young adulthood (age 18 to 30). Furthermore, the sequence of transition events may not be a single pattern, as multiple patterns may exist. Therefore, in an exploratory investigation, the current study identified the heterogeneity of transition patterns regarding multiple life events.

Class enumeration and model evaluation

To select the number of classes, a number of criteria were investigated as discussed in the analysis plan. Information criteria continued to decrease as the number of latent classes increased (Table 3) and might have suggested six classes were needed if such models were fit, based on selecting the model with the highest LL. This may be partly due to the large sample size, supporting the extraction of additional latent classes (Dean et al., 2013). However, the five- and six-class solutions did not replicate the highest log-likelihood value, which indicates the
existence of local maxima. Thus, those two solutions were excluded from consideration as the optimal class model. Of the remaining classes in consideration as the optimal model, the four-class solution had the smallest SSABIC and AIC values. Also, the statistically significant LMR-LRT value for this solution indicates that it is a significant improvement compared to the three-class solution. The smallest class size in the four-class solution and the entropy value (.72) were acceptable. Thus, after examining the hazard and lifetime distribution functions more carefully, the four-class solution was selected as the optimal model as it was able to most parsimoniously and effectively describe heterogeneity in the risk of the events over time.

--- Insert Table 3 About Here ---

Transition Pathways to Adulthood (Heterogeneity in the Timing and Sequence of multiple transition events).

Unstructured hazard probabilities (i.e., instantaneous event timing, \( \hat{h} \)) and lifetime distribution probabilities (i.e., cumulative hazard probability, \( \hat{D} \)) of each class are shown along with the class descriptions. Furthermore, the median event age (when the lifetime distribution function was equal to 0.50) of each transition event within a latent class is also shown in table 4. To aid in understanding cumulative hazard probability at specific age points, the lifetime distribution probability at age 18, 24, and 30 is also provided in table 5.

--- Insert Tables 4 and 5 About Here ---

The first class (n = 6,839, 47.2%) was characterized by an early risk of employment, followed by transitioning into family formation. Hazard probabilities and lifetime distribution probabilities of this class are as follows:
The risk of full-time work was the highest at early ages ($\hat{h}_{\text{age}18} = .55$) and then rapidly decreased by age 22 ($\hat{h}_{\text{age}22} = .12$). The rest of the risks consistently decreased until age 30 ($\hat{h}_{\text{age}30} = .02$). The median age for beginning full-time work was less than age 18 (see table 4), with
a .92 of lifetime distribution probability by age 24, which indicates that 92% of youths belonging to this class had engaged in full-time work by age 24 (see table 5). Family formation transitions occurred next, such as marriage and parenthood. Both the risk of marriage and parenthood was low at early ages, but moderately increased until their mid-twenties. For example, the risk of marriage was low at an early age ($\hat{h}_{age^{18}} = .01$), but moderately increased until the mid-twenties ($\hat{h}_{age^{25}} = .07$ [the peak risk]). Then, the risk decreased by age 30 ($\hat{h}_{age^{30}} = .03$). In a similar manner, the risk of parenthood was also low in their early twenties ($\hat{h}_{age^{18}} = .02$), but moderately increased until their mid-twenties ($\hat{h}_{age^{25}} = .08$ [the peak risk]). Then, the risk decreased by age 30 ($\hat{h}_{age^{30}} = .05$). During the study period (ages 18 to 30), the risk of marriage was never higher than .09 for any age, nor was the risk of parenthood. However, the median age of parenthood was between 29 and 30 (see table 4). More importantly, the lifetime distribution probabilities of transitioning into marriage and parenthood were .49 and .52 by age 30, indicating that half of youths belonging to this class married and had a first child by age 30 (see table 5).

On the contrary, the risk of college graduation was consistently low throughout all of the time periods. In detail, the risk of college graduation was never higher than .04 for any age. The median age for college graduation was more than 30 years with a lifetime distribution probability of .25 by age 30, indicating that only 25% of youths belonging to this class graduated college by age 30. Given the early risk of full-time work combined with the moderate increase in family formation risk in their mid-twenties, the first class was labeled an “early work and then family formation” class.

The second class (n = 3,731, 25.7%) was characterized by an increasing risk of full-time work, followed by college graduation by the mid-twenties, and a consistently low risk of
transitioning into any family formation during the study period. Hazard probabilities and lifetime distribution probabilities for this class are displayed as follows:

Panel a. Hazard probability (instantaneous timing of event)

Panel b. Lifetime distribution probability (cumulative hazard probability)

Class 2: Work/education with no family (n = 3,731, 25.7%)
The risk of beginning full-time work was low until age 20 ($\hat{h}_{age20} = .04$) and increased from age 20 ($\hat{h}_{age20} = .18$) to age 25 ($\hat{h}_{age25} = .37$). Then, the risk decreased again until age 30 ($\hat{h}_{age30} = .05$). The median full-time work age was between 21 and 22 (see table 4), with a lifetime distribution probability of .96 by age 30 ($\hat{D}_{age30}$), indicating that 96% of youths in this group engaged in full-time work by age 30 (table 5). College graduation “risk” also followed a similar pattern during the mid-twenties. For example, the risk increased from age 21 ($\hat{h}_{age21} = .03$) and tended to peak at age 23 ($\hat{h}_{age23} = .30$). The risk then decreased by age 30 ($\hat{h}_{age30} = .02$). The median college graduation age was between 23 and 24 (see table 4). A lifetime distribution probability of transitioning into college graduation by age 30 of .69 indicated that 69% of youths in this class graduated college by age 30 (see table 5). On the contrary, this class had a low risk of transitioning into a family formation (marriage or parenthood) at all ages. For example, the risk of marriage was less than .05 for all ages, and the risk of transitioning into parenthood was similarly low, peaking at .02 at age 29. By age 30, a .28 lifetime distribution probability of transitioning into marriage was detected (see table 5). The lifetime distribution probability of becoming a parent was only .12 (see table 5). The median ages for both marriage and parenthood were more than age 30 (see table 4). Taking into account this information, the second class was labeled a “work and education with no family formation” class.

The third class ($n = 2,677, 18.5\%$) was characterized by a relatively high risk of early full-time work, followed by family formation (such as marriage and parenthood), with a low “risk” of college graduation at all ages. Hazard probabilities and lifetime distribution probabilities of this class are as follows:
The risk of beginning full-time work was the highest at age 18 ($\hat{h}_{age18} = .56$) and rapidly decreased by age 24 ($\hat{h}_{age24} = .08$). Then, the risk remained low until age 30 ($\hat{h}_{age30} = .05$). The median age of beginning full-time work was less than age 18 (see table 4). Lifetime distribution
probabilities of beginning full-time work increased by .88 until age 24, indicating that 88% of youths belonging to this group had already experienced full-time work by age 24 (see table 5). Family formation events, such as first marriage and becoming a parent, came next. For example, compared to the risk of full-time work from the early- to mid-twenties, the risk of being a parent at or before age 18 was lower (\( \hat{h}_{\text{age8}} = .37 \)), but this risk decreased less until age 25 (\( \hat{h}_{\text{age25}} = .27 \)). The median age of parenthood for this group was between ages 18 and 19, which is later than the corresponding median age for full-time work (see table 4). Furthermore, the lifetime distribution probability of parenthood increased more from age 18 to age 24 (\( \Delta \hat{D}_{\text{age8–24}}: .56 \) [= .91−.37]) compared to corresponding probability of beginning full-time work for the same time period (\( \Delta \hat{D}_{\text{age8–24}}: .32 \) [= .88−.56]), which indicates that more youths belonging to this class became a parent than began a full-time work from ages 18 to 24 (see table 5). In a similar manner, the risk of marriage at age 18 was lower (\( \hat{h}_{\text{age8}} = .22 \)) and consistently decreased until age 30 (\( \hat{h}_{\text{age30}} = .06 \)). However, the median marriage time point of this group was between ages 20 and 21, which is later than corresponding median for beginning full-time work (see table 4). Also, the lifetime distribution probabilities of marriage increased more from age 18 to age 24 (\( \Delta \hat{D}_{\text{age8–24}}: .41 \) [= .63−.22]) compared to corresponding probability of beginning full-time work during the same time period (\( \Delta \hat{D}_{\text{age8–24}}: .32 \) [= .88−.56]), which indicates that more youths belonging to this class married than began full-time work from ages 18 to 24 (see table 5). On the contrary, youths belonging to this class remained at consistently low “risk” of college graduation by age 24 (maximum \( \hat{h}_{\text{age24}} = .04 \)). The median time point of college graduation was more than age 30 (see table 4), with a relatively small lifetime distribution probability of
graduating college by age 30 ($\hat{D}_{age30} = .20$; see table 5). This low cumulative probability indicates that most youths belonging to this class did not experience college graduation during the study period. Therefore, the third class was labeled an “early work and early family formation” class.

Panel a. Hazard probability (instantaneous timing of event)

Panel b. Lifetime distribution probability (cumulative hazard probability)

Class 4: Conventional pathway (Work/education and then family; n = 1,256, 8.7%)
The fourth class (n = 1,256, 8.7%) was characterized by a moderate risk of transitioning into both college graduation and full-time work in the early- and mid-twenties, followed by an increasing risk of transitioning into marriage and parent roles in the late twenties. Hazard probabilities and lifetime distribution probabilities for this class are displayed above. More specifically, the risk of college peaked in the early twenties (at age 22 \( \hat{h}_{age22} = .50 \)) and rapidly decreased in the mid-twenties (\( \hat{h}_{age27} = .01 \)). The median age of college graduation was between ages 21 and 22 (see table 4), with a .83 lifetime distribution probability by age 24, indicating that 83% of youths belonging to this class graduated college by age 24 (see table 5). Then, the risk of full-time work increased. That is, the risk of beginning full-time work was the highest in their mid-twenties (between ages 22 \( \hat{h}_{age22} = .51 \) and 24 \( \hat{h}_{age24} = .52 \)). The median age of beginning full-time work was between ages 21 and 22 (see table 4), with a .91 lifetime distribution probability by age 24 (see table 5). The risk of transitioning into family formation came next. For example, the risk of marriage for these class members was relatively low in their early twenties \( \hat{h}_{age22} = .20 \), but steadily increased and peaked in their mid-twenties (at ages 26 \( \hat{h}_{age26} = .56 \)). The median age of marriage was between 22 and 23 (see table 4), with a .99 (nearly 1.00) lifetime distribution probability of marriage by age 30 (see table 5). The risk of parenthood was the last risk to peak. The risk of parenthood was low in their early twenties \( \hat{h}_{age23} = .05 \), but moderately increased until age 30 (\( \hat{h}_{age30} = .33 \) for the peak risk of parenthood). The median age of parenthood was between 26 and 27 (see table 4), which was the latest median age of the four transition events for this class. A high lifetime distribution probability of .87 was found at age 30, indicating that 87% of youths in this class became a parent by age 30 (see table 5). Given that most of the youths belonging to this class experienced all four transition events,
which fits with the social norms and expectations of adult roles, the fourth class was labeled a “conventional adulthood (education/work and then family formation)” class.

**The influence of Early Contextual and Individual Characteristics on Transition Pathways (the Timing and Sequence of Multiple Transition Events)**

**Investigating the correlation matrix and descriptive statistics among predictors**

To ensure that the effects of numerous predictors were due to unique variances, the current study explored multicollinearity among study predictors at Wave 1. The correlation matrix and descriptive statistics are shown in table 6. All predictors were correlated in the expected direction. Furthermore, most of correlations across all predictors were small and acceptable, with the exception of one modest contemporaneous correlation between problem behavior and deviant peer affiliation ($r = .32, p < .001$). In order to take into account this correlation, the current study controlled for this effect by incorporating the correlation between problem behavior and deviant peer affiliation in all of the regression models tested. The skewness among predictors ranged from -1.07 to 2.05, which is within acceptable limits (George & Malley, 2009).

--- Insert Table 6 About Here ---

**The influence of early cumulative socio-economic adversity on transition pathways (the timing and sequence of multiple transition events)**

Next, using a multinomial logistic model, the current study investigated how early cumulative socio-economic adversity influenced the transition pathways. At Wave 1, 279 (0.2%) individuals who were older than 18 years were excluded from subsequent analyses. Thus, the total sample size for subsequent analyses was reduced to 14,224 ($=14,503–279$). The results are shown in tables 7 through 9 (see step 1).
Consistent with previous findings, our results also showed that early cumulative socio-economic adversity strongly influenced the heterogeneity in transition pathways. For example, compared to youths following a conventional transition pattern (i.e., the reference group; see table 7), youths with other two transition patterns (i.e., “early work and early family” and “early work and then family”) were more likely to report higher levels of early cumulative adversity ($\beta$s = .53 [odds-ratio:1.70] and .31 [odds-ratio=1.36], $p <.001$, respectively). Using the percent change formula (i.e., $100 \times \left[\exp (\text{logistic coefficient}) -1\right]$), each coefficient can be interpreted as the percent change in the odds for each one-unit increase in the independent variable (Allison, 2012). Thus, this can be interpreted as: for every one unit increase in cumulative socio-economic adversity, the predicted odds of belonging to the early work and early family pattern or the early work and then family pattern increased approximately 70% (=100 × [exp (.53) – 1]) and 36% (=100 × [exp (.31) – 1]), respectively.

On the contrary, youths belonging to the work/education with no family transitions pattern reported similar levels of early cumulative adversity as those in the conventional pathway class ($\beta = .01$ [odds-ratio=1.01], $p = .11$). Interestingly, as shown in table 8, compared to youths in the early work and early family transition (reference group), those in the early work and then family pattern and the work/education with no family transitions pattern were less likely to report early cumulative adversity (see table 8; $\beta$s = -.17 [odds-ratio=.84] and -.50 [odds-ratio=.61], $p <.001$). These results indicate that for a one unit increase of cumulative adversity, the predicted odds of belonging to the early work and then family pattern decreased approximately 16% (=100 × [.84 – 1]) and the predicted odds of belonging to the work/education with no family transitions pattern decreased 39% (=100 × [.61 – 1]). Also, as shown in table 9, youths following the
work/education and no family transitions pathway pattern were less likely to report early cumulative adversity ($\beta = -0.32$ [odds-ratio=.72, $p < .001$]) compared to members of the early work and then family pattern. This means that for a one unit increase in cumulative adversity, the predicted odds of being a member of the early work and then family pattern decreased approximately 28% ($=100 \times (.72 - 1)$).

In general, the results suggest that membership in the early work and early family pattern and the early work and then family pattern are largely determined by early cumulative socio-economic adversity. Interestingly, experiencing early cumulative adversity does not appear to differentiate youth with a work/education with no family transitions pattern from youth who follow a conventional transition pattern (Pseudo $R^2 = .00$; see table 7).

**The influence of individual characteristics on transition pathways (the timing and sequence of multiple transition events)**

The unique influences of five individual characteristics (i.e., general future orientation, impulsivity, depressive symptoms, problem behavior, and deviant peer affiliation) on heterogeneity in transition pathways were also detected. By incorporating these five individual characteristics to the model, the effect of cumulative adversity was reduced (not shown in the tables), but the reductions were ignorable because the $p$-values were similar. The results are shown in table 7 through 9 (see step 2). The unique association (i.e., main effects) are described below:

**General future orientation.** Compared to youths with a conventional transition pattern, youths of all other transition patterns were more likely to have a lower general future orientation (see table 7; $\beta s = -0.06$ [odds-ratio=.94], -0.08 [odds-ratio=.94], $p < .001$, and -0.02 [odds-ratio=.98], $p < .05$ for early work and early family, early work and then family, and work/education with no
family transition patterns, respectively). However, compared to youths in both the early work and early family pattern as well as the early work and then family pattern, youths with the work/education with no family transitions pattern were more likely to report a higher general future orientation (see table 8 and 9; \( \beta_s = .04 \) [odds-ratio=1.04] and \( .07 \) [odds-ratio=1.07], \( p < .05 \), respectively).

**Impulsivity.** Compared to youths with conventional transition pattern, youths of all other transition patterns reported more impulsivity (see table 7; \( \beta_s = .04 \) [Odds-ratio=1.04], \( p < .001 \), \( .02 \) [Odds-ratio=1.02], and \( .02 \) [Odds-ratio=1.02], \( p < .05 \) for “early work and early family””, “early work and then family”, and “work / education with no family patterns”, respectively). Also, youths of work / education with no family pattern were less likely to report impulsivity than those of early work and early family pattern (\( \beta = -.02 \) [odds-ratio=.98], \( p < .05 \)).

**Depressive symptoms.** The results showed that depressive symptoms in adolescence predicted membership in most of the transition patterns. For example, compared to youths with a conventional transition pattern, youths belonging to the early work and early family class were more likely to report depressive symptoms (see table 7; \( \beta = .02 \) [odds-ratio=1.02], \( p < .05 \)). Furthermore, compared to youths in the early work and early family class, youths of both the early work and then family pattern and the work/education with no family transitions pattern were less likely to report depressive symptom (see table 8; \( \beta_s = -.03 \) [odds-ratio = .97] and -.04[Odds-ratio = .96], \( p < .001 \), respectively). Furthermore, youths belonging to the work/education with no family transitions class reported fewer depressive symptoms than those with the early work and early family pattern (see table 9; \( \beta = -.02 \) [odds-ratio=.98], \( p < .05 \)).

**Problem behavior and Deviant peer affiliation.** Given the modest correlation between problem behavior and deviant peer affiliation, the current study estimated all coefficients after
controlling for the association between these two variables. Regarding problem behavior, the results illustrated that youths in all three non-conventional groups (i.e., “early work and early family”, “early work and then family” and “work/education with no family”) reported higher problem behaviors than those in the conventional patterns (see table 7; βs = .03 [odds-ratio = 1.03], p < .01, .03 [odds-ratio = 1.03], and .04 [odds-ratio = 1.04], p < .001 for “early work and early family”, “early work and then family” and “work/education with no family”, respectively). The effects of deviant peer affiliation were similar to those of problem behaviors, but deviant peer affiliation typically exerted stronger influences on transition patterns than problem behaviors. For example, similar to the effects of problem behaviors, youths belonging to both the early work and early family pattern and early work and then family pattern also reported higher levels of deviant peer affiliation than members of the conventional pattern (see table 7; βs = .07 [odds-ratio = 1.07] and .05[odds-ratio = 1.05], p < .001, respectively). Furthermore, youths in the early work and early family pattern and work/education with no family transition patterns reported less deviant peer affiliation than youth in the early work and early family pattern (see table 8; βs = -.02 [odds-ratio = .98] and -.07[odds-ratio = .93], p < .001, respectively). In addition to these effects, the results showed that youths in the work/education with no family transition pattern were less likely to report deviant peer affiliation compared to those in the early work and then family pattern (see table 9; β = -.05 [odds-ratio = .95], p < .001).

In summary, the results showed that general future orientation and deviant peer affiliation were the most influential predictors on transition pattern class membership, followed by impulsivity and depressive symptoms. After controlling for these effects, problem behaviors had only a modest influence on transition patterns (only three statistically significant coefficients; see table 7).
Comparing the effects between contextual and individual characteristics.

By entering one contextual predictor (i.e., cumulative socio-economic adversity) first, followed by five individual characteristics as predictors, the current study investigated which predictors had the strongest influences on transition patterns. Both the contextual effect and the individual characteristics influenced the likelihood of experiencing most transition patterns. However, when considering the effect size of each predictor, the individual characteristics generally had small effects (average $\Delta \text{pseudo } R^2 = .05$ [minimum $\Delta \text{pseudo } R^2 = .01$, maximum $\Delta \text{pseudo } R^2 = .10$]) after controlling for the contextual effect (average $\text{pseudo } R^2 = .13$ [minimum = .00, maximum =.26]), suggesting that contextual effect is a more influential determinant of transition patterns than individual characteristics.

The moderating effect of individual characteristics on the association between cumulative socio-economic adversity and transition pathways.

Furthermore, using mean-centered predictors, several interaction terms were created and then added to the main effect models. In order to avoid multi-collinearity issues, each interaction effect was estimated separately. When adding each interaction term to the main effect model, the main effects of cumulative adversity and five individual characteristics only changed slightly (not shown in the tables). These changes were ignorable because the $p$-values remained similar. For statistically significant interactions, the simple slope was estimated along with a crossover point test. All crossover points fell outside of the range of cumulative adversity values (i.e., the focal predictor), indicating that the simple slopes did not cross each other (shown in figures 6, 7, and 8). The interaction results are shown in tables 7 through 9 (see step 4a − 4e in tables 7, 8, and 9). Also, figures 6 through 8 illustrate the interaction effects. Moderating effects are described below:
Early cumulative socio-economic adversity × General future orientation.

Four statistically significant interaction effects involving general future orientation were detected across the transition pattern models. To examine the shape of these interactions in more detail, the current study conducted simple slope tests. For example, Panel a of figure 6 depicts a graphical representation of the interaction effect between cumulative adversity and general future orientation for early work and early family pattern. The threshold (1.36) of being in the early work and early family transition pattern when youths were in the low levels of general future orientation was significantly higher than the corresponding one (.19) when youths were in the high levels of general future orientation ($t$-value: 6.82, $p < .001$). However, as cumulative adversity increased, youths in the high levels of future orientation group had a 58% higher ($= 100 \times [exp(.46)-1]$) odds of being in the early work and early family pattern compared to the conventional pattern. Instead, youths in the low levels of future orientation group had a 37% higher ($= 100 \times [exp(.32)-1]$) odds of being in the early work and early family pattern compared to the conventional pattern. Thus, youths with high levels of general future orientation were generally more sensitive to cumulative adversity than those with low levels of general future orientation, suggesting a ceiling effect of interaction.

Another example can be found in table 8 (shown as the graph in panel c of figure 7). The threshold (.25) of being early work and early family pattern when youths in the high levels of general future orientation was significantly higher than the corresponding one (-.42) when youths were in the low levels of general future orientation ($t$-value: 6.19, $p < .001$). However, as cumulative adversity increased, youths in the high levels of general future orientation had a 37% lower ($= 100 \times [exp(-.45)-1]$) odds of being in the work/education with no family transition.
pattern compared to the early work and early family pattern. However, youths in the low levels of general future orientation had a 28% lower ($= 100 \times [exp(-.35)-1]$) odds of being in the work/education with no family transition pattern compared to the early work and early family pattern. Thus, youths with high levels of general future orientation were generally more sensitive to cumulative adversity than youths with low levels of general future orientation, suggesting a floor effect of interaction.

*Early cumulative socio-economic adversity × Impulsivity.*

Three statistically significant interaction effects involving impulsivity were detected across the transition pathway models. One of these significant effects is shown in table 7 (see panel b of figure 6). The threshold (.60) of being in the early work and early family transition pattern when youths were in the high levels of impulsivity was significantly higher than corresponding adversity intercept (.13) at low levels of impulsivity ($t$-value: 4.72, $p < .001$). However, as cumulative adversity increased, youths in the high levels of impulsivity group had a 46% higher ($= 100 \times [exp(.38)-1]$) odds of being in the early work and early family pattern compared to the conventional pattern. Instead, individuals in the low levels of impulsivity group had a 75% higher ($= 100 \times [exp(.56)-1]$) odds of being in the early work and early family pattern group compared to the conventional pattern. Thus, less impulsive youths were more sensitive to the influence of cumulative adversity, representing a ceiling effect. The other two significant interaction effects had a similar shape to panel b of figure 6 (i.e., ceiling effects).

*Early cumulative socio-economic adversity × Depressive symptoms.*

Three statistically significant interaction effects involving depressive symptoms were detected across the transition pathway models. One example is shown in table 7 (see panel c of figure 6). The threshold (.79) of being in the early work and early family transition class when
youths were in the high levels of depressive symptoms group was significantly higher than corresponding one (.09) when youths were in the low levels of depressive symptoms group (t-value: 7.36, \( p < .001 \)). However, as cumulative adversity increased, youths in high levels of impulsivity group had a 41\% higher (\( = 100 \times [\exp(.35)-1] \)) odds of being in the early work and early family pattern compared to the conventional pattern. Instead, individuals in low levels of impulsivity group had a 71\% higher (\( = 100 \times [\exp(.54)-1] \)) odds of being in the early work and early family pattern group compared to the conventional pattern. This finding suggests a ceiling effect where cumulative adversity less influenced youths with high levels of depressive symptoms compared to those with high levels of depressive symptoms.

Another example can be found in table 9 (shown as the graph in panel a of figure 8). The threshold of being work/education with no family pattern when youths were in the low levels of depressive symptoms (-.16) was significantly higher than the corresponding one (-.54) at high levels of depressive symptoms (t-value: -4.72, \( p < .001 \)). However, as cumulative adversity increased, youths in the high levels of depressive symptom group had a 23\% lower (\( = 100 \times [\exp(-.27)-1] \)) odds of being in the work/education with no family pattern compared to the early work and then family pattern. Instead, individuals in the low levels of depressive symptom group had a 28\% lower (\( = 100 \times [\exp(-.34)-1] \)) odds of being in the work/education with no family pattern compared to the early work and then family pattern. This is suggestive of a floor effect, indicating low depressive youths were more sensitive to cumulative adversity.

*Early cumulative socio-economic adversity \( \times \) Problem behavior.*

Three statistically significant interaction effects were detected involving problem behavior across several transition pathway models. One example is shown in table 7 (see panel d of figure 6). The threshold (1.09) of being in the early work and family transition pattern when
youths were in the high levels of problem behavior was significantly higher than corresponding one (.17) when youths were in the low levels of problem behavior ($t$-value: 7.72, $p < .001$).

However, as cumulative adversity increased, youths in the high levels of problem behavior group had a 55% higher ($= 100 \times [\exp(0.44)-1]$) odds of being in the early work and early family pattern compared to the conventional pattern. Instead, youths in the low levels of problem behavior group had a 70% higher ($= 100 \times [\exp(0.53)-1]$) odds of being in the early work and early family pattern compared to the conventional pattern. That is, youths with high levels of problem behaviors were less sensitive to cumulative adversity than those with low levels of problem behaviors, suggesting a ceiling effect of interaction.

Another example can be found in table 8 (shown as panel a of figure 7). The threshold (.62) of being in early work and then family pattern when youths were in the low levels of problem behavior was significantly higher than the corresponding one (.47) when youths were in the high levels of problem behavior ($t$-value: -2.32, $p < .05$). However, as cumulative adversity increased, youths in the high levels of problem behavior group had a 17% lower ($= 100 \times [\exp(-0.19)-1]$) odds of being in the early work and then family pattern compared to the early work and early family. Instead, youths in low levels of problem behavior group had a 12% lower ($= 100 \times [\exp(-0.13)-1]$) odds of being in the early work and then family pattern compared to the early work and early family. The shape of interaction suggests the amplification effect, indicating that youths in the low levels of problem groups were less vulnerable to disrupted transition pattern compared to those in the high levels of problem groups.

*Early cumulative socio-economic adversity $\times$ Deviant peer affiliation.*

Four significant interaction effects were detected for deviate peer affiliation across the transition pathway models. One example is shown in table 7 (see panel e of figure 6). The
threshold (1.31) of being in the early work and then family pattern when youths were in the high levels of deviant peer affiliation was significantly higher than corresponding one (.81) when they were in the low levels of deviant peer affiliation ($t$-value: 5.67, $p < .001$). However, as cumulative adversity increased, youths in the high levels of deviant peer affiliation had a 32% higher ($= 100 \times \exp(.28) - 1$) odds of being in the early work and then family pattern compared to the conventional pattern. Instead, youths in low levels of deviant peer affiliation had a 40% higher ($= 100 \times \exp(.34) - 1$) odds of being in the early work and then family pattern compared to the early work and early family. This suggests a ceiling effect where youths with high levels of deviant peer affiliation were influenced less by cumulative adversity compared to those with low levels of deviant peer affiliation.

Another example is shown in table 8 (see panel d of figure 7). The threshold (.56) of being in the work/education with no family pattern when youths were in the low levels of deviant peer affiliation was significantly higher than the corresponding one (-.18) when youths were in the high levels of problem behavior ($t$-value: -7.22, $p < .05$). However, as cumulative adversity increased, youths in the high levels of deviant peer affiliation had a 45% lower ($= 100 \times \exp(-.61) - 1$) odds of being in the work/education with no family pattern. Instead, youths in the low levels of deviant peer affiliation had a 33% higher ($= 100 \times \exp(-.41) - 1$) odds of being in the work/education with no family pattern compared to the early work and early family. The other two interactions have similar patterns (see panel b in figure 6 and panel b in figure 7).

**Gender and race/ethnicity differences.**

In general, female were more likely to experience transition patterns that included early family formations compared to male. For example, females were more likely to experience the conventional pattern than the “early work and then family transition” pattern and the
“work/education with no family transition” pattern (see table 7; $\beta$s = -.34 [odds-ratio= .71] and -.25 [odds-ratio = -.78], $p < .001$). However, females were more likely to be members of the early work and early family transition class than the conventional pattern (see table 7; $\beta$ = .33 [odds-ratio= 1.39] $p < .001$). In a similar manner, females were less likely to be in non-family-oriented formation patterns (i.e., early work and then family pattern and work/education with no family transition pattern) compared to the early work and early family transition,; see table 8; $\beta$s = -.72 [odds-ratio= .48] and -.58 [odds-ratio= .56], $p < .001$). These results suggest that females were more likely to complete family formation at earlier ages compared to males. Interestingly, females were also more likely to experience the work/education with no family transition pattern compared to the early work and then family pattern (see table 9; $\beta$ = .12 [Odds-ratio= 1.12], $p < .001$), which indicates that males often began full-time work earlier than females.

In general, youths reporting a minority racial/ethnic status (i.e., Black and Hispanic) were less likely to experience the conventional transition pathway. For example, both Blacks and Hispanics were more likely to be members of the “early work and early family transition”, the “early work and then family transition”, and the “work/education with no family transition” (see table 7; $\beta$s = .39, .26, .and 48, $p < .001$ for Blacks; $\beta$s = .24, .27, $p < .001$, and 20, $p < .05$ for Hispanics) than Whites. Furthermore, Hispanics were less likely to experience the “work and education with no family transition” compared to both the “early work and early family transition” (see table 8; $\beta$ = -.30, $p < .001$) and the “early work and then family transition” (see table 9; $\beta$ = -.24, $p < .001$). Contrary to Blacks and Hispanics, Asians were more likely to experience a conventional transition pathway. For example, Asians were less likely to be in the “early work and early family transition” compared to “conventional transition pattern” (see table 7; $\beta$ = -.28, $p < .05$). Also, compared to their odds of being in the “early work and early family
transition”, Asians were more likely to be in both “early work and then family pattern” (see table 8; \( \beta = .28, p < .001 \)) as well as the “work/education with no family transition pattern” (see table 6; \( \beta = .73, p < .001 \)). Interestingly, Asians were more likely to be in the “work/education with no family transition pattern” compared to the “conventional transition pattern” (see table 7; \( \beta = .48, p < .001 \)).
2.5 Discussion

Given timing and sequence of multiple transition events (i.e., graduate college, full-time work, marriage, and parenthood), the current study employed a multivariate discrete-time survival model (MDTSM) approach to examine dynamic patterns of adult roles transition from adolescence to young adulthood in a longitudinal, nationally representative sample of adolescents (n=14,503). This advanced method provides unique information by characterizing individuals according to the timing and sequence of multiple events. The findings of the current study are described as follows:

Summary

**Heterogeneity of multiple life transition patterns (Hypothesis 1).**

In overall sample, the risk of full-time work showed dynamic patterns while other three transition events were consistently low and flat from ages 18 to 30. However, using multivariate discrete-time survival model (MDTSM) as an exploratory analytical tool, the current study identified four distinct transition patterns such as early work and then family (n=6869, 47.2%), work/education with no family pattern (n=3731, 25.7%), early work and early family pattern (n=2677, 18.5%), and conventional pattern (n=1256, 8.7%). Consequently, hypothesis 1 was supported by data.

**The influences of early cumulative socio-economic adversity on heterogeneity of multiple life transition patterns (Hypothesis 2).**

Using multinomial logistic model approach, the current study inserted an early cumulative socio-economic adversity to the model to investigate the effect of early contextual risk factor on four distinct transition patterns. The results showed that early cumulative adversity influenced most of transition patterns with high effect sizes, suggesting the early cumulative socioeconomic
adversity largely determine the youths’ pathway to adulthood. However, non-significance p-value of cumulative adversity was detected in comparison between conventional pattern and work/education with no family formation pattern, indicating cumulative adversity did not distinguish between these two transition patterns. Consequently, the second hypothesis of the current study was partially supported by data.

**The influences of early individual characteristics (i.e., future orientation, impulsivity, depressive symptoms, problem behavior and deviant affiliation exposure) on heterogeneity of multiple life transition patterns (Hypothesis 3).**

Next, the current study entered five individual characteristics (i.e., future orientation, impulsivity, depressive symptoms, problem behavior, and deviant peer affiliation) to the model to investigate how individual uniquely influence the heterogeneity in transition patterns. The results showed that most of individual characteristics influenced four transition patterns. Among five predictors, general future expectation and deviant peer affiliation influenced most transition patterns. These two individual characteristics distinguished more disrupted transition patterns (i.e., early work and early family pattern) from conventional pattern and less disrupted transition patterns (i.e., work/education with no family pattern). Depressive symptoms in adolescence also influenced some of transition patterns. Interestingly, when compared to youths in conventional transition pattern, depressive symptoms more influenced youths in precocious maturity transition pattern (i.e., early work and early family pattern). However, depressive symptoms significantly distinguished among most of non-conventional transition patterns. For example, the results showed that depressive symptoms had a weaker influence on early work and then family pattern and work/education with no family pattern than early work and early family pattern.
Furthermore, depressive symptom had weaker influences on work/education with no family than early work and then family formation.

Instead, impulsivity and problem behavior distinguished non-conventional patterns from the conventional patterns. For example, both individual characteristics had weaker influences on all three non-conventional patterns than conventional pattern. Instead, those two individual characteristics failed to distinguish among three non-conventional patterns (Except that impulsivity less influenced work/educational with no family than early work and early family formation pattern). The effect sizes of individual characteristics were relatively small across most of transition pattern models after controlling for main effects of contextual risk factors (i.e., cumulative socio-economic adversity). Given the results of the current study, the third hypothesis of the current study was partially supported by data.

The moderating effects of individual characteristics on the association between early cumulative socio-economic adversity and life transition patterns (Hypothesis 4).

The current study entered interaction terms to the model to investigate not only addictive effects of a cumulative socioeconomic adversity and individual characteristics, but also multiplicative effects between a cumulative socioeconomic adversity and individual characteristics on transition patterns. The current study detected many interaction effects, indicating that youths of high risk individual characteristics were less influenced by cumulative adversity while those of low risk individual characteristics were more influenced by cumulative adversity (i.e., ceiling effects). However, deviant peer affiliation and cumulative adversity interacted with some transition patterns as an amplification pattern (or fanning pattern) when comparing among non-conventional patterns (see panel b and d of figure 7). For example, low deviant peer affiliated youths were less likely to be in early work and early family formation
compared to high deviant peer affiliated youths. The effect sizes of interaction effects were relatively small across most of transition pattern models after controlling for main effects of context and individual predictors. Given the results of the current study, the third hypothesis of the current study was partially supported by data.

**The difference of Gender / ethnicity influence transition patterns (Hypothesis 5).**

By adding gender and ethnicity variables to the model, the current study examined how gender and ethnicity influence transition patterns. The results showed that females were more likely to engage in early family formation (such as “early work and early family”). For example, as expected, although females were more likely to be in the convention pattern compared to the low-family formation patterns (i.e., “early work and then family”, and “work/education with no family”). On the other hands, youths in the “early work and early family” pattern were more likely to be female compared to those of “conventional transition” pattern. Youths in the “early work and early family” pattern were more likely to be female compared to those of all other transition patterns (i.e., “conventional transition”, “early work and then family”, and “work/education with no family” patterns).

Next, race/ethnicity also influenced to form multiple transition patterns. Black and Hispanic youths were more likely to follow the non-conventional patterns compared to white. Instead, Asian were more likely to be in the convention pattern or at least partial conventional pattern. For example, Asian were more likely to be in the convention pattern or work and education with no family pattern (school-work transition on time) than in the early work and early adult role patterns (i.e., “early work and early family” and “early work and then family”). Given the results of the current study, the third hypothesis of the current study was partially supported by data.
Understanding the Research Findings

The heterogeneity in timing and sequence of multiple transition events

The current study hypothesized the heterogeneity in the timing and sequence of four transition events (i.e., college graduation, full-time work, marriage, and parenthood). Using an exploratory approach (i.e. person-centered approach), this hypothesis was strongly supported, as results indicated a four class model in which groups were differentiated largely by their periods of peak occurrence risk. That is, the early risk pattern of beginning full-time work, and then family formations (i.e., “early work and then family” pattern) was identified as the most common transition patters in this sample (n=6839, 47.2%). Then, individuals whose periods of the highest risk for full-time work and college graduation in early twenties, but the low risk of family formation (i.e., “work / education with no family formation” pattern) came next (n=3731, 25.7%), followed by individuals whose the period of the early risk for full-time work, marriage, and parenthood (i.e., “early work and early family formation” pattern; n=2677, 18.5%). Then individuals whose the period of the highest risk for college graduation and full-time work in early twenties, marriage in mid-twenties, and parenthood in late-twenties (i.e., “conventional transition” pattern) were the smallest class (n=1256, 8.7%).

Life course theory emphasized the timing and sequencing of transitions (Amato et al., 2008; Elder, 1998). Transitions have different meanings, precursors, and consequences depending on when individuals occur in the life course and where they fit within larger sequences. Overall, the current study found the existence of variation in multivariate hazard functions, median time points of events, and lifetime distribution functions which discriminated among groups of individuals. This variations of multivariate survival functions provided the evidence that each transition events have different timing which in turn influences the occurrence
of other events. Consistent with this notion, the four classes were identified in the current study. For example, many of youths were identified as *early work and then family formation*, which is characterized by youths who began full-time work in early ages and engage in family formation (n = 6839, 47.2%). This class showed that the risk of full-time work in early ages (at age 18 [peck age]) while the risk of family formation behaviors (i.e., marriage, and parenthood) were consistently low, but stable for all ages. Also, most of youths in this class did not experience college graduation until late-twenties. Consistent with the findings of the current study, Osgood, Ruth, Eccles, Jacobs, and Barber (2005) also identified the youths who were characterized by least advanced in their progression into adult roles by age 24 (i.e., youths who were largely employed [most of youth hold low-level service jobs], but less educated, less married, and no children). They labeled those youths as the *slow starters*. In our results, youths of this class only showed high proportion of early employment by age 24 (92%) while a moderate portion of youth engaged in family formation (i.e., marriage [29%] and parenthood [30%]) and low proportion of college graduation (9%) by age 24. Compared to youth of other three classes (“*work/education with no family*”, “*early work and early family*”, and “*conventional transition*” patterns), youths of this class do not seem to be placing themselves in a strong position to succeed when the time comes to enter adult roles. Arnett (2000) suggested that adult-role delayed youths can be seen as representing another version of emergent adulthood, for they have not assumed most of the conventional roles of adulthood, and they are, perhaps, in an extended period of exploration.

The *work and education but no family formation* class (n = 3731, 25.7%) identified in the current study can be another good example to describe the timing and sequence of multiple events. Most youths in this class began the full-time work in early-twenties (from ages 21 to 22; median point of full time work). Youths then graduated the college in mid-twenties (from ages
23 to 24; median point of full time work). Thus, youths in this class were more likely to be employed before completing school. Interestingly, the sequence of this transition pattern is opposite to conventional school-to-work transition pattern (i.e., work careers being after the completing of formal schooling; Hirshman & Voloshin, 2007). Furthermore, most of youths belonging to this class only completed these two transition events (beginning full-time work and college graduation) in early- and mid-twenties. Then, they did not involve in family formation such as marriage and parenthood until late-twenties (i.e., delayed family formation). Existing research on school-to-work transition reported that shifting social and economic conditions over the last three decades have diminished the centrality of the conventional route of school leaving and entry into employment (Bynner, 2001; Dorsett & Lucchino, 2014; Pollock, 2007). Therefore, the sequence of school-to-work transition have become more individualized (Dorsett & Lucchino, 2014). Consistent with this notion, Hirshman and Voloshin (2007) reported that many college students are employed simultaneously to support their consumption and related lifestyle activities. This overlapped transition pattern implies that some of youths hold jobs even before graduating college.

Life course literatures have consistently reported that early career commonly produces negative consequence such as poor academic performance and school dropout (Staff, Woolnough, Silver, Burrington, & Vaneseltine, 2012). More importantly, early career tends to be unstable with low salary (Mortimer, Vuolo, Staff, Wakefield, & Xie, 2008). Furthermore, those positions are unrelated to their actual interests (Hirschman & Voloshin, 2007). However, Schneider and Stevenson (1999) emphasized the importance of postsecondary degrees to achieve successful vocational objectives. Thus, early-career youths may overcome the negative effect of early career and graduate the college to achieve career-goal. Consistent with this notion, Vuolo,
Staff, and Mortiner, (2012) reported that some of these early employed youths graduate college in order to move from “unstable jobs with low salary” to “stable jobs with high salary” in their quest for a good person–job fit. Shulman and Nurmi (2010) suggested that those youths who overcome the negative effects of early career pursue high levels of goal-oriented action. Thus, given the rapid economic change and increasing turbulence in the labor market, youths of this class may prefer to spend more time to achieve career-goals (e.g., stable jobs with high salary) than those of other class. For this reason, youths belonging to this class may be more likely to be career-oriented or goal-oriented compared to those of other class. Therefore, they may postpone the family formation such as marriage and parenthood until they achieve the career goal.

Existing findings support this idea. Gustafsson and Kalwij (2006) reported that individuals who are more carrier-oriented delay first birth. Also, Martin and Bumpass (1989) reported that educated individuals marry late. The current study clearly show the existence of these types of transition patterns.

The current study also identified the *early work and early family formation* class (n = 2677, 18.5%). Most of youths belonging to this group experienced full-time work in early ages (at age 18). Therefore, this risk pattern was somewhat similar to the first class. However, most of youth in this class also experienced early family formation such as early marriage and early parenthood, which in turn, influence low levels of college graduation while youths of the first class did not experience early family formation such as early marriage and early parenthood. Instead, small proportions of the first class consistently married and had a first child after mid-twenties. Consistent with the finding of the current study, existing research has consistently reported the effects of the employment timing on other transition events. For example, Staff, and colleagues (2012) showed the detrimental effects of teenage employment. According to their
findings, the experience of early working foster a sense of adult independence and a perception that they are no longer “Children” in the parental home (Gold-scheider & DaVanxo, 1989). Thus, early employment can lead to early residential independence from parents, which is associated with greater freedom form parental control and weaker ties to parents (Longest & Shanahan, 2007). Thus, youths increase the likelihood of early family formation behaviors (i.e., early marriage and early parenthood; Long-more, Manning, & Giordano, 2001), which also increase the likelihood of school drop-out (Lee & Staff, 2007; Monahan, Lee, & Steinberg, 2011). Previous studies have reported this early work–family transition as a precocious maturity (Staff et al., 2012; Wickrama, Conger, Lorenz, & Jung, 2008). The current study clearly showed the evidence that the early timing of employment leads to early family formation (labeled as “Early work and early family formation”).

Fourth identified class can be characterized by completing college and beginning the full-time work in early- and mid-twenties and engaging in family formation such as marriage and parenthood in mid- or late-twenties (n = 1256, 8.7%). The current study labeled this class as the conventional pattern of transition events. In this class, most of youths experienced all four transition events “on-time” (based on national averages timing of transition events) which influence the occurrence of other transition events on-time. Interestingly, the class size is relatively smaller than other three classes. This small class size may reflect individualized life course in the current society (Oesterle et al., 2010). Thus, many youths may not follow conventional patterns of transition events. Consistent with previous finding, the current study also identified the small proportion of conventional pattern of transition events.

The influence of contextual effect on transition patterns.
Using a single cumulative adversity index, the current study examined how early family and socioeconomic contexts influence transition patterns from adolescence to adulthood (ages 18 to 30). The results clearly showed that early cumulative adversity strongly influenced most of transition patterns, especially, non-conventional patterns. In detail, early employment transition pattern (i.e., early work and early family pattern, and early work and then family pattern) were determined by early cumulative adversity, suggesting that the more adversities youth experienced in early ages, individual development had evolved to respond in an accelerated fashion, which put youths at risk for beginning full-time work in early ages (subjective weathering; Foster, Hagan, & Brooks-Gunn, 2008). Interestingly, although cumulative adversity had strongly influences on most transition patterns, this powerful predictor did not distinguish work/education with no family formation from conventional transition pattern, suggesting that youths in both patterns were less influenced from early cumulative adversity. This evidence supports the description of work/education with no family formation. Although youths of this class did not experience family formation, they completed school-to-work transition in a timely manner. Also, youths in work/education with no family formation may be more likely to be goal-oriented. Thus, although these youths experienced early cumulative adversity, they may compensate for early disadvantages with their future-oriented motivation. Consistent with this notion, Seery and colleagues (2010) suggested the effect of inoculation effect; early adversity may foster some of individual’s resilience to protect negative developmental consequence and maintain a healthy outcome (Rutter, 2012). According to their suggestion, some of youths who have high levels of future-oriented (i.e., goal-oriented) may overcome their background adversities. Furthermore, Damian et al. (2014) recently found that positive personality traits lead
youths to compensate the main effect of early adversity. The current study empirically replicated these previous suggestions using multiple transition patterns.

**The influence of individual characteristics on transition patterns.**

In general, the result showed that general future expectation and deviant peer affiliation were the most influential predictors, followed by impulsivity and depressive symptoms. After controlling for these effects, problem behaviors had modest influences on transition patterns. Regarding the future expectation, youths who have high levels of future expectation were more likely to be in convention patterns compared to other non-convention patterns. Interestingly, compared to youths of work/education with no family formation, those of convention pattern were likely to have higher levels of future expectation. This result may be caused by the measures of general future orientation. The current study used a composite mean scores of general future expectation containing three dimensions of future orientation: (a) education future orientation, (b) life future orientation, and (c) marriage future orientation (Chen & Vazsonyi, 2011). Thus, this composite mean score of future orientation takes into account three different future expectation. For this reason, the general future expectation used in the current study were more associated with convention pattern rather than associated with work/education with no family formation characterized by goal-oriented youths. The deviant peer affiliation was detected as another powerful individual characteristic predictor. Given the association between deviant peer affiliation and problem behaviors, the current study investigated unique effects of both predictors. Interestingly, the results showed that deviant peer affiliation were stronger associated with transition pattern compared to problem behaviors.

Developmental theories have suggested that susceptibility to peer influence are important contributors for youths’ developmental consequences (Monahan et al., 2009). More importantly,
delinquent adolescents become more accepted by their peers during adolescence (Moffitt’s taxonomic theory; 1993). As the deviant youths become more acceptable, non-delinquent adolescent may copy not only deviant peer’s delinquent behaviors, but also deviant peers’ disorganized life style (e.g., unplanned life style) in order to increase feelings of group cohesiveness (behavioral synchrony; Dong, Dai, & Wyer, 2015). According to Moffit’s theory (i.e., adolescence-limited antisocial behavior; 1993), most of youths diminish delinquency in late-adolescence or early-twenties. For this reason, problem behaviors in adolescence may not strongly predict transition patterns in adulthood. However, those youths still maintain disorganized life styles which came from deviant peer. This disorganized life styles may have long-term effects on individual development, which put youths at risk for being in disrupted transition patterns. Consistent with this notion, the current study showed that problem behaviors had smaller effect to predict transition patterns than deviant peer affiliation across multiple transition models.

Furthermore, impulsivity distinguished all non-conventional transition patterns from conventional transition pattern, indicating that youths in all non-conventional transition patterns were more likely to be impulsive than those of convention pattern. Interestingly, the results also showed that youths of early work and early family formation were more likely to be impulsive compared to work/ education with no family formation, indicating that youths of work /education with no family formation more control the responsiveness to the immediate rewards compared to those of early work and early family transition formation. This finding may serve as another evidence that youths of work / education with no family formation were less impulsive compared to youths in the other non-conventional patterns. Also, the results showed that depressive symptoms more influenced early work and early family formation pattern (i.e., precocious
maturity) compared to other transition patterns. This was consistent with previous findings (Wickrama et al., 2014)

Regarding the effect size (pseudo R-square and odds-ratios) of individual characteristics, the results showed that five individual characteristics in the current study predicted most of transition patterns. However, total effect sizes of individual characteristics were smaller compared to those of a contextual predictor (i.e., cumulative socio-economic adversity), suggesting that the effects of early environmental context (i.e., early cumulative socio-economic adversity) on multiple transition patterns were still powerful (i.e., main effect) even after controlling for individual characteristics. Consistent with the finding of the current study, Cicchetti and Toth (2005) reported that early cumulative adversity is a powerful predictor of human development outcomes such as psychosocial adjustment in adulthood. The current study extended the findings of previous study by identifying that early cumulative adversity strongly influence multiple transition pattern even after controlling for individual characteristics. This finding implies that transition patterns to adulthood are influenced by personal resources, but more influenced by their early socio-economic environments.

The moderating effects of individual characteristics on the association between early cumulative socio-economic adversity and life transition patterns.

The current study also detected many moderating effects of individual characteristics on the association between cumulative adversity and multiple transition patterns. However, contrary to my expectation, the most significant interactions was not detected as fanning patterns or amplification effect (DiPrete & Eirich, 2006). Instead, the shape of interaction was detected as ceiling effects for exposure to adolescent adversities, indicating that a stronger effect of positive individual characteristic (e.g., higher levels of future expectation, and low levels of impulsivity
and depressive symptoms, etc.) in the presence of low levels of cumulative adversity, and a weaker effect of negative individual characteristics (e.g., lower levels of future expectation, and high levels of impulsivity and depressive symptoms, etc.) in the presence of higher levels of cumulative adversity. This complex relationship between cumulative adversity and individual characteristics reflects that the effect of cumulative adversity are more prominent in youths with positive individual characteristics, but not in youths with negative individual characteristics.

Most individual characteristics interacted with cumulative adversity as ceiling effects, indicating the youths with positive individual characteristics were more sensitive to early cumulative adversities. However, the current study also detected some amplification interaction effects (fanning effect) between deviant peer affiliation and cumulative adversity. For example, the results showed that low levels of deviant peer affiliation were less influenced by cumulative adversity while high levels of deviant peer affiliation were more influenced by cumulative adversity. These results are broadly consistent with a diathesis-stress model (Monroe & Simons, 1991; Zuckerman, 1999); the youths with a vulnerability (i.e., high levels of deviant peer affiliation) are more likely to be in disrupted transition patterns (i.e., early work and early marriage or early work and then family formation) when they were exposed to negative contexts (i.e., early cumulative adversity). This relationship between cumulative adversity and deviant peer affiliation reflects that the negative effect of cumulative adversity are more prominent at high levels of deviant peer affiliation.

The effect sizes (i.e., pseudo R-square and Odds-ratios) of interaction effects were smaller than those of cumulative adversity and individual characteristics. This small effect sizes of interaction effects reflected the low power of interaction effects.

The influence of gender and race / ethnicity group on transition patterns.
**Gender difference**

The results showed that female were more likely to engage in transition patterns compared to other non- or low levels of family formation patterns (i.e., early work and then family formation and work / education with no family pattern). This results were consistent with previous finding (Räikkönen, Kokko, Chen, & Pulkkinen, 2012). However, the results also indicated that when compared to youths of early work and early family pattern, youths of convention pattern were less likely to be female, indicating the female were more likely to engage in early family formation compared to male. In line with the findings in the current study, Sandefur et al (2005) suggested the importance of gender difference in the link between marriage and parenthood during young adulthood. Given their suggestions, the gender difference in the timing of family formation (i.e., marriage and parenting responsibilities) are likely to differently influence men’s and women’s transition patterns. According to the findings in the current study, female early engaged in early family formation compared to male. Consequently, females were more likely to have moved into the adult family roles (as indicated by living with children) in early ages compared to male. At similar time, this early family formations lead female to begin full-time work to support their family in early ages, rather than enter to college. Consistent with this notion, Oesterle et al (2010) suggested that female are more likely to than men to transition into multiple adult roles compared to male. The results clearly showed that female were more likely to experience multiple events simultaneously in early ages (by age 24) compared to male.

**Race / ethnicity difference**

The current study detected the racial and ethnic difference of transition patterns. The results showed that Blacks and Hispanics were more likely to be in non-convention patterns (early work and early family, early work and then family, and work/ education with no family
patterns) compared to Whites. This result was consistent with previous findings. For example, Forste and Tienda (1992) reported that Blacks are more likely to be in early family formation (early marriage and early parenthood) which serves at a barrier to school completion. They also reported that early marriage affect school completion only for whites, but not blacks and Hispanics. All these results implies blacks and Hispanics were more disadvantaged when they moved into the adult roles. Interestingly, the results showed that Asians were less likely to in vulnerable transition pattern. For example, Asian youths were more likely to be in work / education with no family pattern than any other transition patterns. This may imply the Asian youths were more likely to be goal-oriented or career-oriented compared to other ethnicity. Consistent with this notion, Mau and Bikos (2000) found that when controlling for school, familial, and individual variables (such as self-esteem), Asian students had higher occupational aspirations than their white counterparts. Furthermore, a U.S. Census data by the Population Reference Bureau (2000) reported that higher proportion of Whites and Asians hold higher status jobs and college degrees compared to African American and Hispanic adult. However, few studies have adequately examined this possibility. Future studies need to investigate the difference of racial and ethnic identities on multiple transition patterns in detail.

Limitations and future works for the current study

Although findings from the present study are generally consistent with the hypothesized model, several factors potentially limit the scope and generalizability of the results. First, future study should involve the consequence of transition patterns. The current study identified the multiple transition patterns and investigated how early contextual effect and individual characteristics addictively and multiplicatively influence the formation of transition pattern. However, youths in multiple transition patterns may have different consequence. For example,
Mouw (2005) suggested that different pathways affect different adult outcomes such as socioeconomic attainments, health (mental and physical health), and relationships with family or romantic partner. Second, the current study only defined transition to adulthood using four transition events (such as college graduation, full-time work, marriage and parenthood). However, there may be many other events which influence adulthood pathways. For example, many alternative type of marriage may exist such as cohabitation which are more associated with risk for divorce and marital distress (Jose, O’Leary, & Moyer, 2010). Thus, cohabitation may differently influence the timing of other transition events. Otherwise, this cohabitation may not exist sequentially with other transition events. Third, the depressive symptoms measure used in the present study only assessed symptoms present during the past week. Future studies should use more clinical measures of depression. Fourth, the current study assumed that all antecedents in the current study have stable effect during the adolescence to young adulthood. Thus, those were treated as Time Independent Covariate (TIC). However, those effects of antecedents may change over time, suggesting the role of Time Dependent Covariate (TVC). Then, those time effects may differently influence transition patterns. Fifth, the accelerated cohort-sequence design which the current study hired may inadequately recovers information concerning the full longitudinal data from different cohort segments. This different cohorts may impact to assess the transition events. In order to control this cohort effects, future study replicates the findings using a single cohort sample Finally, non-observed genetic components and contextual effect multiplicatively influence precocious development (Wickrama et al., 2014), suggesting the genetic information may be also associated with other transition patterns in the current study. Therefore, future studies should explore these risk factors in greater detail.

Implications for the current study
Life course theory posits that the early adversity have long-term effects on individual developmental consequence. The current study extended this perspective by investigating early adversity influence the timing of transition events in young adulthood, which influence to shape other transition events. The findings from current study suggested that early adversity put youths at risk to be in non-conventional patterns (early or late occurrence of transition events) which influence to occur other transition events (i.e., sequence of transition events). The current study provides a useful context for understanding how early contextual effect and personal resources influence to move into adult roles from adolescence to adulthood (heterogeneity in pathways to adulthood).

In addition, the identification of members of four transition patterns and the early risks of these group members provides a potentially useful prognostic tool for early preventive/intervention efforts, treatment, and policy formation. Particularly, these multiple groups not only provide information about how youths move into adult roles, but also about how early antecedents influence to shape multiple transition patterns. This information enables the development of unique interventions targeting these specific groups. Such interventions should (a) eradicate or weaken early social and individual risks including family (both family socioeconomic adversities and negative family processes) and contextual (e.g., community SES) disadvantages, and (b) promote and develop individual resiliency components to avoid non-conventional patterns. These intervention tasks emphasize the need for agencies and organizations at different levels and in various settings to work together towards the common goal of reducing youths’ disrupted transition pattern. Similarly, these findings highlight the need for federal, state, and local level policies to have integrated effort to lead youths into the right transition pathways.
CHAPTER 3. STUDY 2
Developmental Continuity and Discontinuity of Psychopathology in the Transition Period to Young Adulthood: The Moderating Roles of Life Transition Patterns

3.1 Introduction

Previous psychological assessment research has reported that externalizing (EXT) such as delinquency and internalizing (INT) such as depressive symptom and anxiety symptoms are represented as two domains of psychopathology in adolescence (Reitz, Beković, & Meijer, 2005). However, past research has not fully taken into account the role of substance use (SUB) such as smoking, which typically peaks in the developmental period of adolescence and young adulthood (Chen & Kandel, 1995). More recently, Verona, Javdani, and Sprague (2011) reported the three factor model (i.e., externalizing, internalizing symptoms, and substance use) as the best-fitting model to describe psychopathology in adolescence. Given the high levels of comorbidity among each specific symptom, these three distinct domains (externalizing, internalizing symptoms, and substance use) may represent the existence of comorbidity at a higher level in adolescence (Krueger, 1999; Reitz et al., 2005).

The Longitudinal General Factor Structure of Psychopathology in Adolescence

In order to address the comorbidity in adolescence psychopathology, Lahey et al. (2004) argued that higher–order factors of internalizing psychopathology (e.g., depressive symptoms) and externalizing psychopathology (e.g., delinquency) should be defined based on the correlations among the specific dimensions of psychopathology. Furthermore, past studies suggested that a higher order structure of specific dimensions is needed to account for the co–
occurrences among depressive symptoms, antisocial behavior, and substance use problems (Mesaelle, Stice, & Hogansen, 2006). These previous findings support the idea that the comorbidity among INT, EXT, and SUB in adolescence can be explained by higher-order factor structures.

More importantly, this hierarchical structure may exist in a longitudinal context. That is, trajectories of general psychopathology symptoms (GPS) can be identified as a higher-order factor capturing the shared variance of INT, EXT, and SUB in adolescence. Consistent with research suggesting that co-occurrence reflects more combined effect of multiple risk factors (Oland & Shaw, 2005), Leadbeater, Thompson, and Gruppuso (2012) reported that adolescents who started high in one domain symptoms were also consistently high in the other domain symptoms at each assessment point. These stable co-occurrences at each time point among symptoms levels across time suggest that general psychopathology is stable in adolescence. Furthermore, the developmental literature has reported similar trajectories of specific symptoms. For example, INT such as depressive symptoms and anxiety have been reported as a slightly convex shaped from adolescence to young adulthood (Kim, Capaldi, & Stoomiller, 2003). Similar to INT, Moffitt (2006) showed that most delinquency of normative youths temporarily increased during adolescence and decreased in late adolescence (i.e., adolescence-limited perspectives). Furthermore, Chen and Jacobson (2012) reported that smoking increases from early adolescence to early-twenties, and then declined thereafter. The similar developmental patterns of depressive symptoms, delinquency, and smoking imply the existence of the longitudinal structure of GPS in adolescence. Despite the evidence of the longitudinal structure of GPS in adolescence (from ages 15 to 18), less is known the higher-order factor structure of GPS in adolescence. Given the findings from previous studies, the current study investigated the
longitudinal factor structures of general psychopathology using internalizing, externalizing symptoms and substance use in adolescence (ages 15 to 18).

**Longitudinal Dimensionality of Psychopathology from Adolescence to Young Adulthood**

The differentiation perspective (Sroufe & Rutter, 1984) posits that the dimensionality of psychopathology increase over time from being mostly unidimensional (undifferentiated; inflating diagnostic comorbidity rates) in infancy to evidencing as many dimensions of psychopathology across time (fully differentiated). According to this perspective, the association among specific symptoms diminish when moving into transition period to young adulthood. Hence, general psychopathology may not exist as a higher-order in young adulthood. More recently, using clinical samples, Sterba and colleagues (2010) provided evidence for this notion. They reported that psychopathology started with low dimensionality (i.e., highly correlated with each other or the existence of latent construct) in young children, but increases in dimensionality with age, suggesting that specific domains exist as separated symptoms over time, but not as the latent construct. This evidence implies the developmental change in the factor structure of psychopathology from adolescence to young adulthood. Therefore, the general psychopathology (i.e., higher-order) construct may change with an increase of dimensionality in psychopathology over time. Taking into account differentiation perspective, the current study extends the previous findings by investigating the best factor structure of psychopathology in youth psychopathology (ages 15 to 18) and adulthood psychopathology (ages 30 to 32).

**Developmental Pattern of Psychopathology from Adolescence to Young Adulthood**

*Heterogeneity in trajectories of general psychopathology in adolescence.*

Furthermore, previous studies employing a longitudinal design to examine youth psychopathology generally utilized methods that assume a single population of trajectories for all
adolescents. Previous studies, however, have shown heterogeneity in INT (Costello, Swendsen, Rose, & Dierker, 2008), EXT trajectories (van den Akker, Deković, Asscher, Shiner, & Prinzie, 2013) and SUB (Musci, Uhl, Maher, & Ialongo, 2015). For example, using National Longitudinal Study of Adolescent Health (Add Health), Costello et al. (2008) identified four distinct depressed mood classes consisting of no depressed mood, stable/low, early high/declining, and late/escalating. Wickrama and colleagues (2008) demonstrated similar trajectory classes. Also, using a community male sample (age 12–26 years), Wiesner, Kim, and Capaldi (2005) identified six distinct delinquency classes of depressive symptoms from adolescence to young adulthood. In terms of substance use, Washburn and Capaldi (2015) recently identified three distinct classes of marijuana use in twenties. However, most of the previous studies took into account separated symptoms of general psychopathology trajectories. Consequently, they have not explored the heterogeneity in development of the co-occurrence which takes into account all three specific domains (i.e., internalizing, externalizing, and substance use) simultaneously. Given the evidence of heterogeneity in each separated symptom, the current study anticipated several distinct trajectory classes of general psychopathology in adolescence.

**Transition pattern of Psychopathology from adolescence to young adulthood.**

More importantly, most of previous approaches have also underlined the developmental continuity from adolescence to young adulthood (i.e., quantitative development [linear development]; Moffitt, 1993), suggesting the stable developmental pattern from adolescence to young adulthood. For example, Kim-Cohen and colleagues (2003) showed that EXT such as oppositional defiant and conduct problems were the most frequent antecedents of adult similar problems (i.e., homotypic continuity). However, given the natures of transition period to young adulthood, developmental patterns of psychopathology may also exist as a discontinuous developmental form (i.e., qualitative development; Rutter, 2013) from adolescence to young
adulthood. Arnett (2000) reported the period from high school to young adulthood as “emerging adulthood with a dense life transition (ages 18-25)”, making the case for the view that this period is theoretically and empirically distinct from both adolescence and adulthood. This transition period from adolescence to young adulthood has been thought of as a particularly sensitive period for individual development (Naicker, Galambos, Zeng, Senthilselvan, & Colman, 2013). Thus, developmental patterns of psychopathology may dynamically change from adolescence to young adulthood, suggesting the developmental discontinuity of psychopathology from adolescence to young adulthood. For example, Odgers et al. (2008) found the evidence that about half of youths who had high levels of problem behavior did not continue their antisocial behavior into adult life, pointing to the need to recognize a substantial adolescence-limited group. Wickrama and colleagues (2008) also reported the developmental discontinuities of depressive symptoms from adolescence to young adulthood. Given the evidence of developmental continuity and discontinuity in psychopathology, the current study examines continuous and discontinuous developmental patterns of psychopathology from adolescence to young adulthood (see Figure 1).

The Moderating Role of Life Transition Patterns from Adolescence to Young Adulthood.

Recently, life course research has suggested that the transition to adulthood is characterized by increased heterogeneity in life patterns as many adolescents selects their own transition patterns to young adulthood although life patterns tend to be fairly homogenous during adolescence (Ross, Schoon, Martin, & Sacker, 2009; Schulenberg, & Schoon, 2012). Consistent with this notion, using samples in United Kingdom (average sample age 26), Ross et al. (2009) identified two distinct family structures consisting of “conventional family” (limited college, full
time employed, independent from parents, married or cohabiting, and with children) and “work orientation without children” (college graduate, full – time employed, married or cohabiting, and no children). Also, Schulenberg and Schoon (2012) identified “slow starters (included those with medium to low levels of education, who were single with no children, employed and living with their parents) along with two common structures (i.e., conventional family and work orientation without children). While these previous studies provide valuable insights regarding distinct life transition patterns, they are limited in that they only emphasized the family structure at a specific time point which ignores the timing and sequencing of these multiple transitional life events. Thus, the present study extends previous studies by systematically investigating multiple life transition events occurrence (big 4 markers; delineated entry into adulthood: completing school, beginning one’s career, marrying, and becoming a parent; Shanahan, Porfeli, Mortimer, & Erickson, 2005) during the transition period to young adulthood. The current study will identify potential sub-populations regarding life transition patterns in the nationally representative study sample.

The concept of transition-linked turning points posits that events or experiences that occur during a transition and that may result in the emergence, discontinuation, or alteration of developmental trajectories (Graber & Brooks-Gunn, 1996). This perspective implies the association between the transition events to young adulthood and developmental discontinuity of psychopathology. Given the fact that transitions in different domains, such as education and family, are interdependent within and across time and form social pathways of linked developmental trajectories, the timing of one transition often has cascading different consequences for other transitions (Masten et al., 2005). For example, conventional life transition patterns commonly start with completing school (Sandefur et al., 2005). As a great deal of social
science research has demonstrated over the years, educational attainment is one of main keys to much of what happens to people later in their lives (Hogan & Astone, 1986). The amount and quality of education that a person achieves affects their occupation and career, income, and wealth accumulation, and whom she/he marries as well as many other features of late life (Sandefur et al., 2005). Given the transition-linked turning points perspective, these successive positive–sequences may have proximal influence in reducing psychopathological symptoms or maintaining low levels of the symptoms during the transition period.

However, individuals who experienced these non–conventional life transition patterns (e.g., precocious development and slower starters) are commonly deprived of the opportunity to complete their education leading to non-normative consequences. For example, very early parenting hinders not only entry into postsecondary education (i.e., college education; Upchurch, 1993) and but also increases beginning full-time work in early ages (Macmillan & Eliason, 2003). Like the same mechanisms from positive consequences (i.e., proximal influences), these negative sequence of transition patterns may escalate psychopathology or maintain high levels of the psychopathology during transition period to young adulthood. Although previous findings implied that life transition patterns have moderating roles on psychopathology during the transition period, we know little about how psychopathology are influenced by life transition patterns.

The last purpose of the current study is to investigate the moderating influences of life transition patterns on psychopathology from the adolescence to young adulthood (see Panel B of Figure 3). Consistent with life course perspectives, the current study expects that individual who experienced conventional life transition patterns (education / work transition, followed by family formation) during the transition period to young adulthood may be likely to reduce the symptoms
or maintain low levels of the psychopathological symptoms in young adulthood. However, individuals who experienced non-conventional life transition patterns (e.g., precocious development, and/or slow starter) during this vulnerable period may be more likely to escalate their early psychopathological symptoms or maintain high levels of the symptoms compared to individual who experienced conventional life transition patterns.

Thus, as shown in figure 1, consistent with both developmental psychopathological perspectives and life course perspective, this study extends past research by (a) examining the longitudinal factor structure of psychopathology in both adolescence and young adulthood, (b) identifying transition patterns of psychopathology, and (c) examining the moderating effects of life transition patterns on developmental patterns of psychopathology between adolescence and young adulthood. The current study will estimate life transition patterns by multivariate discrete-time survival mixture model, as described in the first paper.

3.2 Specific Study Hypotheses

This study first identifies transition patterns of psychopathology and then investigates the moderating influences of multiple life transition patterns on the transition patterns of psychopathology. The current study used a Structural Equation Modeling (SEM) framework to analyze data from a longitudinal sample of target adolescents participating in the nationally representative National Longitudinal Study of Adolescent Health (Add Health) to examine heterogeneity of transition patterns of psychopathology from adolescence to young adulthood and the influence of life transition patterns on the transition patterns of psychopathology. Figure 9 depicts my specific hypotheses;

--- Insert Figure 9 About Here ---
**Hypothesis 1.** General longitudinal factor structure of psychopathology exists only in adolescence (ages 15 to 18), but does not exist in adulthood (ages 30 to 32).

**Hypothesis 2.** Multiple transition patterns of psychopathology exists from adolescence to young adulthood.

**Hypothesis 3.** Life transition patterns moderates the transition patterns of psychopathology.
3.3 Method and Measurements

Sample and Data

Data for this study were drawn from a nationally representative sample of adolescents participating in the National Longitudinal Study of Adolescent Health (Add Health). In 1995, baseline (Wave 1) data were derived from a complex cluster-sampling of middle and high school students, yielding 20,745 respondents of 12–19 years of age (average age was 15.5 years), from 134 middle and high schools. To ensure diversity, the sample was stratified by region, urbanicity, school type (public vs. private), racial composition, and size. Second, third, and fourth wave data were collected in 1996, 2001, and 2008 (Wave 2 = 14,738, Wave 3 = 15,170, and Wave 4 = 15,701 sample sizes). The median education of mothers and fathers was high school or GED completion. About 11% of the households received food stamps. More information about Add Health is available at http://www.cpc.unc.edu/ projects/AddHealth. The final sample consisted of approximately 53% women, and 35% of respondents reported a minority racial/ethnic status with the largest percentages reported for African American (15.8%), Hispanic (13.2%), and Asian (6.0%), respectively. Add Health incorporates sampling weights that account for the unequal probability of selection; for proper weighting when conducting time-to-event analyses, weights from the first wave are used, and individuals with missing weights must be removed (Chen & Chantala, 2014). After removing individuals with missing Wave I weight variables (8.8% of the sample), the present study uses data from 14,503 respondents who participated in Wave 1 (with no missing data on age, gender, or race/ethnicity) and provided transition event measures at Wave 4 (2008) when they were aged 25-30.

Measures

Depressive symptoms. Internalizing symptoms were assessed using nine items from the
Center for Epidemiologic Studies Depression (CES-D) scale at all four waves of data collection (Radloff, 1977). Participants were asked “How often was each of the following things true during the past week” (e.g., “You were bothered by things that usually don’t bother you,” “You could not shake off the blues, even with help from your family and friends,” “You felt you were just as good as other people”). Responses options were on 4-point Likert scale ranging from 1 (never or rarely) to 4 (most of the time). The final depressive symptoms variable was the average of the participant’s responses to the nine items. The scale had adequate internal reliability ($\alpha = .80$ or higher at all four waves).

**Delinquency.** The nonviolent delinquency measures covered behaviors with a types of scale widely used in delinquency and violent research (Thornberry & Kronhn, 2000) were closely related to scales used in other Add Health studies (e.g., Guo, Roetter, & Cai, 2008; Hagan & Foster, 2003). To estimates longitudinal patterns of nonviolent delinquency comparable across waves, only items included in all four waves were used. A 5-item 4-point scale was used to measure nonviolent delinquency: In the past 12 months, how often did you deliberately damage property that didn’t belong to you; steal something worth more than 50 dollars; go into a house or building to steal something; sell marijuana or other drugs; steal something worth less than 50 dollars? All items’ response ranged from 0 “never”, 1 “once or twice”, 2 “three or four times” to 3 “five times or more.” A delinquency score were created using the mean of five items. Cronbach $\alpha$ was between 0.66 and 0.74 across four waves.

Repeated delinquency measures were detected as slightly skewed to the right (acceptable range $< \pm 2.00$; George & Mallery, 2009). The data transform (e.g., log-transformation $[\log Y + 1]$ when variables contain 0) can be commonly conducted when study variables are right-skewed (Frone, Cooper, & Russel, 1994). However, Brown (2006) suggested that data transformation of
the skewed variables often encounter two problems: (1) transferred variables often changes their associations with other variables which result in changing other parameters (fit statistics, and parameter estimations); and (2) it makes the interpretability of the parameter estimates more complex. Furthermore, maximum likelihood estimator (known as “ML”) is not reliable when data contains non-normal continuous variables (marked skewness or kurtosis) due to the spurious inflated model $\chi^2$ value (i.e., over-rejection of solution which lead to underestimate standard errors of estimation and fit indices [such as CFI and TLI]) (West, Finch, & Curran, 1995). Brown (2006) recommended MLR estimator (i.e., maximum likelihood with robust standard errors) for non-normal continuous data, which was applied across all models of the current study. This robust ML adjusted standard error and model fit indices (Satorra & Bentler, 1994).

**Smoking.** In each wave, participants reported the number of days in the past month that they had smoked (ranging from 0 to 30 days), and the average number of cigarettes they had smoked each day in the past month (ranging from 0 to 100). For the “number of cigarettes” question, responses > 40 (<1% of the sample) were coded as missing (Chen & Jacobson, 2012). Response for the two items (frequency and amount items) were multiplied to obtain a single measure of total cigarettes smoked in a month (range= 0 – 1080) (Chen & Jacobson, 2012). Then, the item was recoded as a 4-point Likert scale (0 [never] to 3 [between averages 25 and 36 cigarettes per day] to measure average number of cigarettes per day.

**Multiple transition events.** Four role status variables were examined: college graduation, full-time work, marriage, and parenthood (Settersten, 2007). For each age from 18–30, a binary variable for each status is created indicating whether the individual occupied the status for the first time (on-set timing) at that age (coded 1), or had not occupied the status by that age (coded 0). Once the individual occupied one of the role statues, they no longer contributed data for the
remaining ages for that status (coded as missing) (Muthén & Masyn, 2005). To account for the fact that a relative small percentage of individuals occupied one of the roles before they were 18 years old (0.1% youth for college graduation, 5.2% youth for employment, 0.9% youth for marriage, and 3.7% youth for parenthood), the binary variable for age 18 represented whether the individual occupied the status for the first time at age 18 or younger (0.0% youths experienced college graduation before age 18; 0.3% youths experienced first marriage before age 18; 7.0% youths experienced first-full time work before 18; 1.9% youths experienced parenthood before age 18).

The role status variables were taken from the Wave 4 Add Health interview. The year of the respondent’s first degree (associate’s degree or bachelor’s degree) after high school was used to determine the age at which the first post-high school degree was obtained. The age when the person first began full-time work (at least work 35 hours a week) was directly measured in the Add Health interview. The year of the individual’s first marriage was used to find the age of the respondent when they first married. The date of birth of the respondent’s oldest child was used to determine the age at which the respondent first became a parent.

**Analysis Plan**

The main purpose of the current study is to investigate how life transition patterns influence developmental pattern of psychopathology from adolescence to young adulthood. Therefore, age of respondents is essential to estimate longitudinal patterns of psychopathology and adulthood pathways. In order to take into account the ages of respondents, rather than wave, the current study employed an accelerated design in which age equaled the unit of time (Duncan, Duncan, & Strycker, 2006).

**Second-Order Growth Mixture Model: A Factor-of-Curve Model.**
In order to estimate both factor structures of general psychopathology and the heterogeneity in developmental trajectories of general psychopathology in adolescence (ages 15 to 18), the current study used a Second-Order Growth Mixture Model of Factor-of-Curves (SOGMM of a FCM; Wickrama, Lee, O’Neal, & Lorenz, In press), a combined model of Factor-of-Curve Model (FCM) and a second-order growth mixture factor (SOGMM). The SOGMM-FCM allows researchers to investigate distinct developmental trajectories of general psychopathology. Model building process consists of estimating 2 sequential models: (a) Factor-of-Curve Model, and (b) latent class factor. The model building process was described as follows:

**Step 1: Factor-of-Curve Model.** A factor-or-curve model (FCM) allows researchers to examine the associations among primary growth parameters for multiple subdomain trajectories (Duncan et al., 2006). The first step for developing this model is to confirm that each primary growth curve model has been successfully modeled independently (see a primary growth curve models of figure 2). Then, second-order growth parameters (i.e., Intercept and slope factors) can be specified (see second-order growth factors of figure 10). Model fit information was estimated using an absolute fit index such as Chi-Squared and goodness of fit indices such as Root Mean Squared Error Approximation (RMSEA), Comparative Fit Indices (CFI), and Tucker Lewis Index (TLI). For a good model fit, Hu and Bentler (1999) suggested that RMSEA values be close to .06 or below, and CFI and TLI values be close to .95 or greater for model fit. However, for acceptable model fit, Browne and Cudeck (1993) proposed that RMSEA values less than .07 and CFI and/or TLI values in the range of .90 - .95 suggest an acceptable model fit.

--- Insert Figure 10 About Here ---

**Step 2: Estimate a latent class factor.** The latent class factor allows to investigate the
heterogeneity in trajectories of general psychopathology. In order to find the optimal class model, the current study utilized sample-size adjusted Bayesian information criterion (SABIC; lower values are preferred), entropy and average posterior probabilities of each class for class separation (greater than .70 is preferred for entropy [Muthén, 2000]; greater than .70 implies satisfactory fit for average posterior probabilities [Nagin, 2005]), class sizes (a minimum of 5% for the smallest group; Andruff, Carraro, Thompson, & Gaudreau, 2009), and interpretability of identified classes (Nylund, Asparouhov, & Muthén, 2007).

**Latent Class Analysis (LCA).**

In order to estimate heterogeneity in adult psychopathology, the current study used a Latent Class Analysis (LCA) with means of each domain-symptoms from ages 30 to 32 (see adulthood period of figure 1). Due to the lack of available data to estimate growth parameters (i.e., mean and variance of intercept and slope factors) of three primary growth curve models (i.e., depressive symptoms, delinquency, and smoking) in this period, the current study used the mean score from ages 30 to 32 of each domain as class indicators. This was because relatively low mean scores across ages were detected for all three domains (depressive symptoms, delinquency, and smoking), implying a lack of developmental change across ages.

**Latent Transition Model (LTM).**

One of the purposes in the current study is to investigate the transition patterns of psychopathology from adolescence (ages 15 to 18) to young adulthood (ages 30 to 32). In order to investigate the dynamic transition patterns of psychopathology, Latent Transition Model (LTM) was applied (Liu, Lynne-Landsman, Petras, Maysn, & Ialongo, 2013; Nylund, Grimm, Quirk, & Furlong, 2014). The latent transition model incorporated latent class factors of the two developmental periods simultaneously (adolescence and young adulthood; Collins & Lanza,
In order to avoid the model parameters shift problems, the manual 3-step estimation was conducted for the LTM. This approach estimates an unbiased modal class assignment in both GMMs by fixing threshold values of class indicators that account for the classification uncertainty rate. More details on this 3-step approach are available in Nylund et al., (2014).

**Multivariate Discrete-Time Survival Mixture (MDTSM).**

Next, in aiming to fully understand the timing and sequence of multiple life transition events, the current study used a combination of multivariate discrete-time survival model and longitudinal latent class model (LLCM; also known as RMLCA [Repeated measures latent class analysis], Collins & Lanza, 2010), which proposed by Dean, Bauer, and Shanahan, (2013). The main advantages of this analysis is both to handle with censored data (timing of events) and to identify heterogeneity in unobserved sequence of multiple life transition pathways by examining the latent classes that reveal pathways to adulthood, or patterns of the events over time (Shanahan, 2000). More details on this approach are available in Dean et al., (2013).

Finally, the current study conducted a multiple-group test of latent transition model (Collins & Lanza, 2010; Chung, Kim, Hipwell, & Stepp, 2013) to investigate how multiple pathways to adulthood (i.e., life transition patterns) moderates transition patterns of psychopathology from adolescence to young adulthood. Thus, separate LTM analyses by transition patterns to adulthood were conducted.

The use of the analytical procedures takes into account the clustered nature of the data and provides the correct standard error estimates. All analyses will be performed using the Mplus 7.11 statistical software. In order to handle missing cases in the current sample, all analyses were performed under FIML estimation (i.e., Maximum likelihood estimation with robust standard errors [MLR]). The current study used the TYPE=COMPLEX analysis syntax in order to adjust
for potential bias in standard errors and chi-square computation due to the lack of individual independence between observations within schools in the Add Health data.
3.4 Results

Descriptive Statistics

Descriptive statistics (Mean, standard deviations, Minimum value, Maximum value, and Skewness) for all study variables are shown in Table 10. On average, means of depressive symptoms increased in adolescence (until age 18), whereas depressive symptoms generally decreased over young adulthood (until age 32). Also, a similar pattern was detected regarding smoking, which increased in adolescence and then decreased in adulthood. However, the delinquency consistently decreased from adolescence to young adulthood.

--- Insert Table 10 About Here ---

Longitudinal factor structures of general psychopathology in adolescence

Estimate primary growth curve models of depressive symptoms, delinquency, and smoking

In order to investigate the general psychopathology of adolescent, the current study first estimated three primary latent growth curve models of specific domains (i.e., depressive symptoms, smoking, and delinquency). The results were shown in table 11. The model fits of all three individual models indicated the acceptable fit. Both depressive symptoms and smoking increases during adolescence (.01, \( p < .05 \), and \( .13, p < .001 \) for depressive symptoms and smoking, respectively; see table 11). However, delinquency decreased in adolescence (-.02, \( p < .001 \)). However, all variances were significant, suggesting the existence of common variance.

--- Insert Table 11 About Here ---

Estimate factor-of-curve model for general psychopathology

Next, the current study tested the existence of common psychopathology (see figure 10) by specifying two second-order latent growth factors (i.e., intercept and slope) to primary growth
models. In order to estimate growth parameters (i.e., mean and variance) of second-order growth latent factors, the current study used primary growth factors of depressive symptoms as marker variables (Feldman et al., 2009). The model fit was acceptable ($\chi^2$ [df] = 147.64, $p < .001$; CFI / TLI=.96 / .93; RMSEA=.06). Furthermore, all factor loadings were acceptable (loadings [$\lambda$] = .47, .50, and .69, $p < .001$ for common intercept factors of depressive symptoms, smoking, and delinquency, respectively; and .80, .42, and .85 $p < .001$ for common slope factors of depressive symptoms, smoking, and delinquency respectively). The means of second-order intercept and slope growth factors were .614 ($p < .001$) and .01 ($p < .10$), suggesting the increase of predicted general psychopathology in adolescence. More importantly, the variances of second-order intercept and slope factors were significant (.03 and .01 $p < .01$ for the variances of intercept and slope, respectively), suggesting the existence of distinct developmental patterns of general psychopathology in adolescence.

**Heterogeneity in youth general psychopathology**

In order to investigate the heterogeneity in trajectories of general psychopathology in adolescence, the latent class factors were then specified to factor-of-curves model to estimate the heterogeneity of general psychopathology (see figure 10). Given the complex model of SOGMM-FCM, the current study constrained all variances of growth parameters across class to be equal (i.e., variance invariance; Wickrama et al., in press). The results were shown in table 12. The lowest of SABIC indicated the four class is the optimal class model. However, the four class model contained a lower value of entropy compared to the three class model. Furthermore, the four class solution has poor interpretability of classes (the smallest group n =289 [2.2% of total sample]). Thus, the current study retained the 3 class solution as the preferred model of young adulthood (SABIC: 53079.55; Entropy: .84). Average posterior probabilities of all classes were
greater than .85 and entropies more than .85 showed the successful discrimination and classification of classes. Estimated latent class trajectories were shown in figure 11.

--- Insert Table 12 and Figure 11 About Here ---

As shown in figure 11, in adolescence, it appears that the majority of youth belong to one class (i.e., labeled as “consistently low group”, 78.3%), while the remaining youth belong to one of two smaller classes (i.e., labeled as “high and decreasing group” [5.8%] and labeled as “moderate and stable group” [15.9%]). The variances of slope and intercept were constrained to be equal across three classes (.02, *p* < .01 for all three classes’ intercepts and .00, *p* = .56 for all three classes’ slopes).

**Longitudinal factor structures of general psychopathology in adulthood**

Due to the lack of available data to estimate growth parameters of three primary growth curve models in this period, the current study used the mean score from ages 30 to 32 of each domain as class indicators, which hinders the model building process in estimating a higher-order longitudinal factor structure of general psychopathology in adulthood. Although means of repeated delinquency and smoking variables slightly decreased in adulthood (see table 10), those were relatively low, which may not be estimated using latent growth models. Thus, mean scores of each domain may represent well those low scores of each domain instead of estimating growth parameters.

The main purpose of the current study was to investigate whether the longitudinal higher-order factor structure of general psychopathology exists in adulthood (ages 30 to 32). However, observed mean scores of each domain did not allow an estimate of a higher-order factor of general psychopathology. Instead, as a supplementary analysis, the current study conducted a confirmatory factor analysis to investigate a potential general factor of psychopathology in
adulthood using the mean scores of each domain (ages 30, 31 and 32). The results were shown in figure 12. The standardized loading of each domain was relatively low (ranged from .33 to .38, \( p < .001 \)), suggesting the variances are not much shared among three specific domains. This results support the evidence for the exclusion of the latent factor of general psychopathology in adulthood. Instead, the latent class variables were directly used in the model (see adulthood model of figure 9).

--- Insert Figure 12 About Here ---

**Heterogeneity in adult psychopathology**

In order to investigate the heterogeneity in adult psychopathology, the latent class analysis was conducted. Similar to adolescent model, the adult class model also constrained all variances of growth parameters to be equal across classes (i.e., variance invariance; Feldman et al., 2009). The results were shown in table 12. The lowest of SABIC indicated the four class solution was the statistically optimal class model. However, the four class solution has poor interpretability of classes (the smallest group \( n =54 \) [0.5% of total sample]). Although the three class solution also contained relative small group (the smallest group \( n=286 \) [2.8% of total sample]), the current study retained the three class solution as the preferred model of adulthood (SABIC: 13081.84; Entropy: .98) because of the meaningful interpretability of classes. Average posterior probabilities of all depressive symptoms classes were greater than .93 showed the successful discrimination and classification of classes. Estimated latent class model were shown in figure 13.

--- Insert Figure 13 About Here ---

As shown in figure 13, similar to adolescent groups, it appears that the majority of youth belong to one class (i.e., low averages of all domain [labeled as “low psychopathology”], 73.0%),
while the remaining youth belong to one of two smaller classes (i.e., only smoking high [labeled as “high substance use”], 24.0% and high averages of all three domains [labeled as “high psychopathology”], 2.8%). To determine the extent to which the class solution differentiated between groups, a wald-chi test was conducted on the class variables. Differences among three classes were significant for depressive symptoms (overall $\chi^2$ [df] = 171.62 (2), $p < .001$; Post-hoc test ($p < .05$): High psychopathology > High substance use > Low psychopathology).

Differences among three classes were significant for delinquency (overall $\chi^2$ [df] = 494.71 (2), $p < .001$; Post-hoc test ($p < .05$): High psychopathology > High psychopathology = Low psychopathology). Also, differences among three classes were significant for substance use (overall $\chi^2$ [df] = 9407.22 (2), $p < .001$; Post-hoc test ($p < .05$): High substance use > High psychopathology > Low psychopathology).

**Developmental transitions of psychopathology from adolescence to adulthood**

In order to retain the same class probabilities when two classes are estimated simultaneously, the current study first estimated the classification uncertainty rates (misclassification error rates) of class indicators in both adolescence and young adulthood model, and the final LTM was then built using these uncertainty rates regarding two latent class models (i.e., SOGMM-FCM and LCM). The entropy of LTM was .73 which was lower than one of both separated models. However, Muthén (2000) reported that the entropy value was greater than the preferred .70, indicating clear classification and sufficient power to predict class membership. Also, estimated posterior probabilities across all classes were ranged from .73 to .95, indicating at least seventy percentages of the youths in each of these classes did fit the category to which they were assigned (i.e., clearly distinct classes).

In the hypothesized model, the participants were classified into a latent class based on
estimated posterior probabilities. The current study used the PARAMETERIZATION=LOGIT option to estimate how developmental patterns of youth psychopathology influenced psychopathology in adulthood. Table 13 summarized the key outputs of the transition probabilities of psychopathology into two sections: (a) the probability of membership in each of the psychopathology trajectories in adolescence, conditional upon membership in each of the psychopathology patterns in young adulthood; and (b) the joint probabilities of membership of the developmental patterns of psychopathology in both adolescence and young adulthood. The latter one lists all nine possible combinations of adolescence and adult groups with joint probabilities summing to 1.

--- Insert Table 13 about Here ---

Table 13a showed the evidence of dynamic transition patterns of psychopathology from adolescence to young adulthood. For example, most of youth who were in consistently low of general psychopathology remained low psychopathology (low averages of all three domains) in adulthood (i.e., developmental continuity; 82.2%). However, youths in high and decreased group of general psychopathology reduced this probability when they became young adults (ages 30 to 32). That is, they had a 55.8% of being in low psychopathology when they were in early thirties as opposed to 82.2% in adolescent years, while 32.5% of those still remained in high substance use and 11.7% of those were in high psychopathology when they were in adulthood. Interestingly, youths who were in the moderate and stable group also retained higher probabilities of being in the high substance use group (only high level of substance use; a 59.4%) compared to those who were in low psychopathology (low average of all three domains; a 37.0%), and only 3.6% youths remained youths who were in high psychopathology (high average of all three domains) in adulthood. The multinomial model showed similar results.
Compared to youths in the consistently low group, those of the moderate and stable groups were more likely to be in the high substance group (odds-ratio: 4.04, CI = [2.93, 5.57], \( p < .001 \)) and high psychopathology group when they were in early thirties (odds-ratio: 8.41, CI = [7.45, 9.51], \( p < .001 \)), suggesting the general psychopathology in adolescence precipitate as substance use when they became young adults. Also, compared to youths in the consistently low group, those of high and decreased general psychopathology were more likely to be in the high substance group (odds-ratio: 2.93, CI = [2.41, 3.56], \( p < .001 \)) and high psychopathology group when they were in early thirties (odds-ratio: 7.52, CI = [5.45, 10.51], \( p < .001 \)).

Table 13b indicated the combination probabilities of psychopathology between adolescence and adulthood. The probability of being in five of those groups was extremely low, ranging from 0.6% to 3.3% (less than 5%). The other four transition groups with a sample size over 5% were as follows: (1) moderate / stable in adolescence → low psychopathology in adulthood (6.2%), (2) moderate / stable in adolescence → high substance use in adulthood (10.0%), (3) consistently low in adolescence → high substance use (12.2%), and (4) consistently low in adolescence → low psychopathology in adulthood (consistently low pattern, 63.4%). These results clearly showed that latent class membership is changeable in transition period. These results indicated that substantial percentages of youths (22.2%=10.0%+12.2%; see table 13b) of total sample were linked to high substance use in early thirties (ages 30 to 32). Interestingly, among those, 12.2% of youths in consistently low group moved into high substance use group when they were in early thirties.

**The Patterns of Life Transition Events**

Using multivariate discrete-time survival mixture modeling, the current study identified total four distinct life transition patterns: (1) early work and family formation (Slow starter;
47.2%), (2) work / education with no family formation (25.7%), (3) early work and early family formation (i.e., precocious maturity; 18.5%), and (4) conventional patterns (school-to-work transition on time and then family formation; 8.7%). More details on this estimation are available in the result sections of the first study.

The Moderating Effects of Life Transition Patterns on the Developmental Patterns of Psychopathology from Adolescence to Adulthood.

In order to examine the moderating roles of life transition patterns on the developmental patterns of psychopathology from adolescence to young adulthood, the current study conducted the multi-group LTM (Collins & Lanza, 2010). The results were shown in table 14. In general, the results showed that the developmental patterns of psychopathology from adolescence to young adulthood are different depending on the pathways to adulthood (i.e., life transition patterns). That is, the more disrupted transition events youths experienced (i.e., earlier or later), the more youths followed vulnerable transition patterns. For example, table 14d showed the developmental patterns of psychopathology from adolescence to adulthood only among youths who experienced all transition events on-time (i.e., conventional transition patterns). As can be seen, most of youths who were in the consistently low group of general psychopathology remained low psychopathology (low averages of all three domains) in adulthood (i.e., developmental continuity; 92.7%). This proportion was higher than corresponding one (82.7%) of transition patterns in the total sample (see table 14a). More importantly, among youth with conventional transitional pattern, higher probabilities of youths moved into the low psychopathology group even when they were in the vulnerable group of youth psychopathology in adolescence (i.e., “moderate and stable” and “high and decreasing”) compared to corresponding those of the transition patterns in total sample (see table 14a). Furthermore, these
youths (conventional pattern to adulthood) had lower probabilities of being vulnerable psychopathology group in adulthood compared to corresponding those of the transition patterns in total sample (see table 14a). Overall, the results suggest the conventional patterns of adult roles move youths into less vulnerable psychopathology group in adulthood. Interestingly, youth who experienced work/education with no family formation patterns also showed similar developmental patterns of psychopathology from adolescence to young adulthood although they were slightly more likely to be in vulnerable developmental patterns of psychopathology compared to those of conventional transition patterns. This result suggests that school-to-work transition in early twenties also serves as a buffering role to move youth into less vulnerable psychopathology groups when they were in early thirties.

--- Insert Table 14 about Here ---

On the contrary, when adult roles (i.e., life transition patterns) were delayed or came earlier, these transfer probabilities diminished. Table 14c provided the evidence. Among youth who began early full-time work and experienced early family formation (i.e., early marriage and early parenthood; precocious maturity), youth in consistently low group had 77.2% of being low psychopathology group when they were in early thirties. More severely, among youths in same transition patterns of adult roles, youth in moderate and stable psychopathology group had 30.1% of being in the low psychopathology group when they were in adulthood (see table 14c). These two probabilities were smaller than corresponding those (81.8% and 53.5%) among youths in conventional patterns (see table 14d). The current study also detected similar pattern when youths followed delayed adult roles (i.e., early work and then family formation; slow starter, see table 14a). Also, these two off-time transition patterns (i.e., early work and early family pattern and early work and then family formation [slow starter]) retain relatively higher transition
probabilities that moved into more vulnerable developmental patterns of psychopathology from adolescence to young adulthood. For example, among youths in early work and early family formation, youths who were in high and decreased psychopathology group had 12.1% of being in the high psychopathology group in adulthood. This probability is higher than the corresponding one (4.5%) in the conventional pattern model (see table 14d). Also, youth in early work and then family formation (i.e., slow starters) had similar developmental pattern of psychopathology from adolescence to young adulthood. Interestingly, among youths in work/education with no family formation group, youths who were in high and decreased psychopathology also had 10.6% of being high psychopathology group in adulthood, which is a similar proportion compared to two vulnerable transition patterns (*early work and then family formation* and *early work and early family formation*). Across first and second studies, many evidences supported this transition pattern to adulthood is not a vulnerable one. However, this relatively high probability (10.6%) implies that youth/education with no family formation transition patterns have vulnerable transition patterns of psychopathology from adolescence to young adulthood.
3.5 Discussion

The second study employed a latent transition model (LTM) approach to examine developmental patterns of psychopathology from adolescence to young adulthood and the influence of life transition patterns on the developmental patterns of psychopathology, using a nationally representative sample of adolescents (n = 9154). This advanced method provides unique information regarding how pathways to adulthood influence the longitudinal patterns of psychopathology from adolescence to young adulthood. The findings of the current study are described as follows:

Summary

General psychopathology in adolescence and adulthood (Hypothesis 1).

In adolescence, the current study employed the factor-of-curve model to investigate the general factor of psychopathology using three domains (i.e., depressive symptoms, delinquency, and smoking) which is consistent with differentiation perspective (Sroufe & Rutter, 1984). The results clearly identified the general factors in adolescence, but failed to estimate the same second-order factor structures in adulthood. Consequently, hypothesis 1 was supported by data.

The transition patterns of psychopathology from adolescence to adulthood (Hypothesis 2).

The latent transition model provides the evidence of dynamic transition patterns of psychopathology from adolescence to adulthood. The current study identified three distinct developmental patterns of general psychopathology: (1) youths who had consistently low levels of psychopathology in adolescence (labeled as “Consistently low”; n=10216, 78.6%), (2) youths who had moderate levels and stable across time (labeled as “Moderate and stable”; n=2078, 15.9%), and (3) youths who had high levels and decreased psychopathology over time (labeled
as “high and decreasing”; n=748, 5.8%). Also, the three class model were detected as the optimal class model in adulthood: (1) youths who had low levels of depressive symptom, delinquency, and smoking (labeled as “low psychopathology”; n=7359, 73%), (2) youths who had high levels of smoking, but low levels of depressive symptoms and delinquency (labeled as “high substance use; n=2496, 24%), and (3) youths who have relative all high levels of three domains (labeled as “high psychopathology”; n=286, 3.0%). Thus, total nine transition patterns were identified from adolescence to adulthood. In general, most of youths moved into low psychopathology group in adulthood consistent with the notion of ‘adolescence-limited behavioral problems (Moffitt, 1993). Interestingly, youths who were in moderate and stable group were more likely to be in the substance use group when they were in early thirties, suggesting the influence of early psychopathology on later psychopathology, specifically substance use. Although five transition patterns showed low transition probabilities (less than 5%; see table 13b), the other four transition patterns showed adequate proportions. Consequently, hypothesis 2 was supported by data.

The moderating effects of life transition patterns on the transition patterns of psychopathology from adolescence to adulthood (Hypothesis 3).

Next, the current study specified four distinct life transition patterns to adulthood that I identified via the first study (i.e., “early work and then family formation”, “early work and early family formation”, “work/education with no family formation”, and “conventional patterns”) to the model to investigate how life transition patterns influence the transition pattern of psychopathology from adolescence to young adulthood. The current study clearly showed the evidence that youths were more likely to be in low psychopathology group when their transition events were on-time and follow the conventional sequence (i.e., conventional patterns or
work/education with no family formation) while youths were more likely to be in vulnerable transition patterns when transition events came earlier or later than the social norm (i.e., “early work and early family formation” and “early work and then family formation [slow starter]”). Interestingly, youths who were in work / education with no family formation group showed both negative transition and positive transition patterns of psychopathology from adolescence to young adulthood. Consequently, hypothesis 3 was partially supported by data.

Understand the Research Findings

The longitudinal factor structure of general psychopathology.

One of the main hypotheses in the current study was to investigate the existence of general psychopathology only in adolescence, but less likely to be in adulthood. Using a second-order growth curve model (factor-of-curve model [FCM]), the current study confirmed this hypothesis using three specific domains such as internalizing and externalizing symptoms, and substance use. Past literatures have suggested the existence of general psychopathology consisting of two domains such as internalizing and externalizing symptoms (Krueger, 1999). Also, Verona and colleagues (2011) reported the significant roles of substance use to form adolescent psychopathology factor structure. The current study contributes to the extent literatures by identifying the existence of adolescent general psychopathology factors in a longitudinal context using all three specific domains (depressives symptoms, delinquency, and smoking). The results of the current study showed the acceptable factor loadings of each domain to contribute a second-order factor structure of general psychopathology in adolescence. Interestingly, developmental patterns of all three domains were not similar. Estimated mean trajectories of both depressive symptoms, and smoking increased. Instead, delinquency showed a downward trajectory across adolescence. This shape of delinquency may reflect Moffitt’s (1993)
theory that the early adolescence is defined by normative elevations in conduct problems. Those behaviors then decreased in late adolescence and adulthood (limited-adolescence perspective). The decreased developmental patterns of delinquency confirm Moffitt’ theory. In spite of this different mean trajectories among three symptoms, the current study clearly showed the existence of general psychopathology in adolescence, suggesting that increases in each symptom domain were associated with relative increases in all other domains (co-occurring). According to the failure perspective (Capaldi, 1992), developmental failures associated with delinquency (or antisocial behavior) contributed to increasing depressive symptoms simultaneously. Many studies reported that youths with affective disturbances are thought to consume psychoactive substances use for the purpose of self-medication (self-medication hypothesis; Hruska & Delahanty, 2012). The current study confirmed this contemporaneous associations among three domain specific maintained across adolescence by estimating longitudinal factor structures of general psychopathology. However, the current study failed to detect the general psychopathology in adulthood by estimating weak factor loadings in confirmatory factor analysis (CFA). This may suggest that the contemporaneous associations among three domains were not detected in adulthood. Consistent with these findings, differentiation perspectives posits that each domain may have unique variation across time (i.e., increasing dimensionality of psychopathology with age; Sroufe & Rutter, 1984).

**The transition patterns of psychopathology in adolescence and adulthood.**

Using person-centered analytical technique, previous developmental studies have shown the heterogeneity in internalizing symptoms such as depressive symptoms trajectories (Chaiton et al., 2013; Frye & Liem, 2001) and externalizing symptoms trajectories (Mata & van Dulmen, 2012) from adolescence to young adulthood. However, most of studies have not taken into
account two key questions: (1) the heterogeneity of general psychopathology, and (2) the nature of the transition period to young adulthood. Given the evidences of comorbidity among domains and heterogeneity of each domain, the heterogeneity in developmental patterns of general psychopathology may exist. More importantly, the transition period is thought of as a particularly vulnerable period due to educational, relationship and socioeconomic changes that may occur (Naicker et al., 2013). Consequently, the developmental patterns of general psychopathology can change, suggesting heterogeneity in transition patterns of psychopathology during transition period. The current study extended previous findings by taking into account these two questions simultaneously.

The study results identified three distinct developmental patterns of psychopathology in both adolescence and adulthood, which produced total nice combined transition patterns of general psychopathology. According to the findings of the current study, around sixty percentages of the total sample had consistently low levels of psychopathology from adolescence to young adulthood. This is consistent with previous findings using separated domain symptoms (i.e., depressive symptoms; Wickrama et al., 2008). Moreover, using a multinomial logit model, the results showed that youths of vulnerable groups (i.e., high and decreased group, and moderated and stable group) were more likely to remain similar to the vulnerable group (high psychopathology group and high substance use group) in adulthood compared to those of consistently low group, suggesting developmental continuity of psychopathology from adolescence to young adulthood (see table 13a). This implies that psychopathology which formulated in adolescence is a powerful predictor which influences the production of psychopathology in adulthood.

However, the current study also detected discontinuous developmental patterns of
psychopathology from adolescence to young adulthood. For example, 6.2% of total sample moved a vulnerable group (i.e., moderate and stable group) into a non-vulnerable group (i.e., low psychopathology group) (see table 13b). On the contrast, around twelve percent of the total sample moved a non-vulnerable group (i.e., consistently low group) into a vulnerable group “high substance group” (see table 13b). These changed their developmental patterns reflect the developmental discontinuity of psychopathology and, to a certain degree, a change in the class differentiation from adolescence to young adulthood, indicating early psychopathology change their developmental patterns during transition period to young adulthood. Particularly, ‘substance use’ dominating class merges during adult years. This implies the roles of life transition patterns to adulthood on the developmental patterns of psychopathology from adolescence to adulthood, which is discussed in next section.

The moderating effects of life transition patterns on transition pattern of psychopathology from adolescence to young adulthood.

Using a multivariate discrete-time survival mixture model (MDTSM), the current study identified four distinct life transition patterns to young adulthood: (1) early work and family formation (slow starter; 47.2%), (2) work / education with no family formation (25.7%), (3) early work and early family formation (i.e., precocious maturity; 18.5%), and (4) conventional patterns (school-to-work transition on time and then family formation; 8.7%). With these four life transition patterns, the current study conducted multiple-group test of LTM to investigate whether the transition patterns of psychopathology was stable or changed. The results clearly showed that youths were more likely to be in vulnerable groups in adulthood when they experienced non-transitional patterns (i.e., off-time transition patterns), indicating the important role of life transition patterns on the transition patterns of psychopathology from adolescence to
young adulthood. Most of previous life course studies have emphasized the effects of only one- or two separated transition events (e.g., work, marriage or school-to-work transition) on the developmental health consequences (Harris, Lee, & DeLeone, 2010; Mortimer & Staff, 2004). These previous studies have not taken into account the timing and sequence of multiple transition events simultaneously when life transition patterns were identified and how patterns of multiple transition events influence the developmental patterns of psychopathology from adolescence to young adulthood. The current study extends previous findings by taking into account the moderating effects of life transition patterns on the developmental patterns of psychopathology from adolescence to young adulthood. According to the results of the current study, when youths experienced conventional life transition patterns (competed school-to-work transition in early twenties and complete family formation in mid-or late-twenties), most of youths remained consistently low psychopathology group from adolescence to young adulthood (see table 14). However, when youths experienced adult-roles earlier or later than the social norm, their developmental patterns of psychopathology changed into more vulnerable groups in adulthood. For example, the results showed that 15.8% of youths in the total sample moved from consistent low psychopathology group in adolescence into high substance use group in adulthood (in table 13a). However, this proportion was diminished when they experienced conventional life transition patterns (i.e., 6.1%) while corresponding one increased when they experienced early work and early family formation (i.e., 21.4%).

Consistent with the current findings, the life course perspective posits that developmental patterns of psychopathology have ‘turning points’ between two different developmental periods (transition-linked turning points; Wheaton & Gotlib, 1997; Galambos & Krahn, 2008). The current study suggests that life transition patterns with ‘turning points’ influence the change of
developmental patterns of psychopathology from adolescence to young adulthood.

Limitations and future works for the current study

The contributions of the present study should be considered with a few caveats. First, the current study did not estimate trajectories of three domains (i.e., depressive symptoms, delinquency, and smoking) in adulthood due to the lack of available information. Instead, the current study used a composite mean score of each domain from ages 30 to 32. This approach was justified due to the fact that most of symptoms was relative low and stable during this time period and low shared variance among three domains (based on confirmatory factor analysis). Thus, composite mean scores may well represent the developmental pattern. However, in order to estimate more robust growth parameters, future studies should attempt to replicate our results using second-order latent trajectory classes in adult years.

Second, due to excessive zero response of respondents, the slightly right skewness of repeated measures in delinquency may be a source of biased growth parameters. In order to solve this problem, previous methodological studies suggested many different models. For example, data-transformation (log \([Y+1]\)) has been widely used. However, this approach was not employed to interpret growth parameters straightforwardly (Brown, 2006). Also, Frone and colleague (1994) suggest censored data strategy using Tobit regression. According to their suggestion, right skewness data can be recognized as left censored data which allow to use Tobit regression under the latent response variables (\(Y^\ast\)). Also, Olsen and Schafer (2001) suggested using a two-part semi-continuous longitudinal model to analyze two separated models including only continuous responses (i.e., actual their response) and binary response (0 response vs. all other responses). In spite of these available analytical strategy, the current study couldn’t apply these models to factor-of-curve model (i.e., second-order growth curve model) due to the
convergence problems. The future research should be replicated using these additional models to correct skewness for delinquency.

Third, the current study did not control gender effects, and race/ethnicity effects. As the first study showed that females experienced some transition events (i.e., family formation [early marriage and early parenthood] earlier than male did, females may have more vulnerable developmental patterns of psychopathology during transition period to adulthood. In a similar manner, Minorities (i.e., Black and Hispanic) may experience more vulnerable developmental patterns of psychopathology due to their non-conventional life transition patterns. Future studies should replicate the findings of the current study using gender and race/ethnicity intra-group analyses. Fourth, previous studies have suggested that the psychopathology is predicted by non-observed genetic and contextual factors (Fergusson, Horwood, & Boden, 2006). Therefore, future studies should explore these risk factors in greater detail.

Practical implications

The current study provides a useful context for understanding the existence of general psychopathology in adolescence. Examining shared features among depressive symptoms, delinquency, and substance use is crucially important, as the emergence of a single symptom in isolation over one’s lifetime is relatively rare. It is likely that individuals manifest multiple symptoms due to generalized symptom vulnerabilities in adolescence. In addition, the identification of class memberships of general psychopathology in transition period and the moderating influence of life transition patterns provides a potentially useful prognostic tool for early preventive and intervention efforts, treatment, and policy formation. Such interventions should promote and develop resiliency factors, aid in redirecting general psychopathology of youth, and seek to buffer the continuous relationship with psychopathology in adulthood.
Moreover, given the dynamic patterns of psychopathology across transition period, the findings highlight the need for federal, state, and local level policies and programs aimed to prevent adolescent negative pathways to adulthood. In summary, a greater understanding of the transition patterns of general psychopathology from adolescence to young adulthood will be useful for identifying adolescents who are at risk for the risky development of general symptoms instead of specific domain symptoms.
CHAPTER 4. GENERAL CONCLUSION

4.1 Summary

Previous life course research has suggested the mechanisms of long-term influence of early adversities in developmental consequences. Among several mechanisms, the path-dependent mechanism describes well this long-term association (DiPrete & Eirich, 2006). According to this mechanisms, early adversities are critical, and produce proximal outcomes which in turn, influence distal outcomes. Linked to the current studies, the path mechanisms allow researchers to hypothesize early individual and contextual risk factors, increase youth’s psychopathology (proximal consequences) which in turn influence psychopathology (distal consequences) in adulthood (Schulenberg, Sameroff, & Cicchetti, 2004). Consistent with this perspectives, many previous studies demonstrated this long-term persistent associations.

For example, using latent growth curve modeling, Kim and colleagues (2003) found that both early individual and contextual risk factors (e.g., youth’ antisocial behavior and family income) increase depressive symptom from adolescence to young adulthood. These previous findings supported the developmental continuity perspective, suggesting that all individuals in the population develop in the same way from adolescence to adulthood (same regression coefficients). However, these previous conclusions have paid little attention to two essential perspectives: (1) the occurrence of heterogeneous life transition patterns during the transition period to adulthood, and (2) the developmental discontinuity perspective of psychopathology from adolescence to adulthood.
In my dissertation, two separate studies extended the previous findings by addressing these two issues. The first paper investigated the heterogeneity in transition patterns to adulthood and how early contextual and individual factors addictively and multiplicatively influence the distinct transition patterns. The results clearly showed the four distinct transition patterns ("Early work and early family formation", "Early work and then family formation [slow starter]", "Work/education with no family formation", and "Conventional pattern"). Both early cumulative adversities (as a contextual risk factor) and five individual characteristics (i.e., future orientation, impulsivity, depressive symptoms, problem behavior, and deviant peer affiliation) significantly influenced transition patterns to adulthood, but early cumulative adversity was detected as the most significant predictor among several risk factors. The second paper then demonstrated how these four distinct life transition patterns influence the continuity and change in psychopathology from adolescence into adulthood. The results clearly showed the existence of both developmental continuity and discontinuity of psychopathology from adolescence to young adulthood. As hypothesized, the youths in more off-time transition patterns such as ("Early work and early family formation [precocious maturity]", "Early work and then family formation [slow starter]") were more likely to be in vulnerable developmental patterns of psychopathology from adolescence to adulthood compared to those in on-time transition patterns ("Conventional patterns", and "Work/education with no family formation"). The overall conclusion, incorporating these two studies, suggests that early risk factors produce qualitatively different life transition patterns which, in turn, influence different developmental patterns of psychopathology from adolescence to young adulthood (see figure 1).

4.2 Limitations
Although the two studies addressed important issues which previous studies had paid little attention, several limitations still remain. First, the overall model (see figure 1) addressed the moderating roles of life transition patterns on the developmental patterns of psychopathology from adolescence to adulthood. However, the overall model still has potential question regarding mediating roles of life transition patterns on the association of psychopathology between adolescence and adulthood. Few studies tested this possibility. For example, Wickrama and colleagues (2012) found that depression in adolescence predict depression in young adulthood through many transition experiences (such as economic and work stability, work quality, and education attainment). Their findings implied that youth psychopathology influence transition patterns which in turn influence psychopathology in adulthood. The current two studies did not incorporate this potential mediating pathways. Future research should test this possibility.

Second, as can be seen in figure 1, most variables employed in both studies were estimated as latent class variables. For example, the first study treated four binary transition event variables (college graduation, full-time employment, marriage, and parenthood) as latent class indicators to estimate distinct life transition patterns. Also, the second study treated psychopathology variables in both adolescence and adulthood as latent class variables. As a consequence, both studies used those class variables as key variables for analyzing hypothesized models. However, my dissertation ignores the potential possibility of unobserved subpopulations in indicators of contextual predictors used in the first study. Life course perspectives posit that social stratification or social status serves as critical roles and therefore have long-term influences on individual development across time, suggesting the contextual factors exist as a qualitatively different cluster or classes, not a quantitatively different one. This framework provides meaningful insights to estimate unobserved subpopulations of contextual factors.
However, this possibility were not included in the first study because of high computational demand as increasing the number of latent class variables. Thus, future research should test this possibility.

4.3 Practical Implication

Overall conclusion highlights the need of selective prevention and interventions for specific target youths. First, given the long-term influence of early risk factors on psychopathology in adulthood though vulnerable transition patterns, overall conclusion highlight the need to increase the duration of early intervention or prevention program for the life-course persistent youths. Additionally, the results also indicate the need for secondary prevention efforts during the transition period. Developmental discontinuity (such as “turning points” in a life course perspective) is an important evolving area of investigation in the psychopathology field. The influence of related life course concepts, including timing and sequencing of life transition events, individual characteristics, human agency, and social context on developmental patterns of psychopathology and turning points offers a potentially fruitful area of investigation that may increase our understanding of why and how psychopathology re-directs over the long-term. Identified developmental patterns of psychopathology from adolescence to adulthood provides a potentially useful prognostic tool for secondary preventive and intervention efforts, treatment, and policy formation. Understanding the factors and processes involved in psychopathology developmental patterns will help policy makers design programs and researchers and health care professionals to develop and implement more effective intervention strategies.
References


Rutter, M. (2013). Developmental psychopathology: a paradigm shift or just a relabeling?


Table 1. An Example of Data Coding for the Multivariate Discrete-Time Survival Mixture (MDTSM) Model.

<table>
<thead>
<tr>
<th>ID</th>
<th>Age 18</th>
<th>Age 19</th>
<th>...</th>
<th>Age 30</th>
<th>Age 18</th>
<th>Age 19</th>
<th>...</th>
<th>Age 30</th>
<th>Age 18</th>
<th>Age 19</th>
<th>...</th>
<th>Age 30</th>
<th>Age 18</th>
<th>Age 19</th>
<th>...</th>
<th>Age 30</th>
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<tbody>
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<td>0</td>
<td>.</td>
<td>.</td>
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</tbody>
</table>

Note. Dots indicate either an individual who experienced the event at prior age or an individual who dropouts during the study period (Age18 to Age 30).
Table 2. Number of Event Occurrences and Sample Estimated Hazard Probabilities (n=14,503).

<table>
<thead>
<tr>
<th>Ages (Years)</th>
<th>College graduation</th>
<th>Full-time work</th>
<th>Marriage</th>
<th>Parenthood</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Event</td>
<td>Hazard</td>
<td>Event</td>
<td>Hazard</td>
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<td>5,711</td>
<td>.39</td>
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<td>19</td>
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<td>1,681</td>
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<td>20</td>
<td>272</td>
<td>.02</td>
<td>1,085</td>
<td>.15</td>
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<tr>
<td>21</td>
<td>419</td>
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<td>1,253</td>
<td>.21</td>
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<tr>
<td>22</td>
<td>1,316</td>
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<td>1,587</td>
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<td>23</td>
<td>1,311</td>
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<td>24</td>
<td>750</td>
<td>.05</td>
<td>622</td>
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<td>25</td>
<td>510</td>
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<td>379</td>
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<td>26</td>
<td>367</td>
<td>.04</td>
<td>194</td>
<td>.16</td>
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<td>27</td>
<td>331</td>
<td>.03</td>
<td>121</td>
<td>.13</td>
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<td>29</td>
<td>179</td>
<td>.03</td>
<td>28</td>
<td>.06</td>
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<td>30</td>
<td>112</td>
<td>.04</td>
<td>12</td>
<td>.04</td>
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</table>
Table 3. Model Fit Index.

<table>
<thead>
<tr>
<th>Latent class</th>
<th>LL</th>
<th>Number of free parameters</th>
<th>SSABIC</th>
<th>AIC</th>
<th>Smallest class size (%)</th>
<th>Entropy</th>
<th>LMR-LRT (df)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-105,871.65</td>
<td>52</td>
<td>212,076.33</td>
<td>212,076.33</td>
<td></td>
<td></td>
<td>5526.96*** (53)</td>
</tr>
<tr>
<td>2</td>
<td>-103,258.17</td>
<td>105</td>
<td>207,188.79</td>
<td>206,726.34</td>
<td>36.6</td>
<td>.78</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>-102,316.37</td>
<td>158</td>
<td>205,644.62</td>
<td>204,948.75</td>
<td>23.3</td>
<td>.76</td>
<td>1883.59*** (53)</td>
</tr>
<tr>
<td>4</td>
<td>-101,710.22</td>
<td>211</td>
<td>204,771.72</td>
<td>203,842.44</td>
<td>8.7</td>
<td>.72</td>
<td>1212.45*** (53)</td>
</tr>
<tr>
<td>5</td>
<td>-101,436.72a</td>
<td>264</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>-101,174.27a</td>
<td>317</td>
<td>—</td>
<td>—</td>
<td>—</td>
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</tr>
</tbody>
</table>

Note. LL= Log-likelihood; SSABIC=Sample Size Adjusted Bayesian Information Criterion; AIC= Akaike Information Criterion. LMR-LRT=Lo-Mendell-Rubin Likelihood Ratio Test. a = No repeated log-likelihood value (non-convergence).
Table 4. Median Lifetime within Latent Classes.

<table>
<thead>
<tr>
<th>Class</th>
<th>Label</th>
<th>College</th>
<th>Work</th>
<th>Marriage</th>
<th>Parenthood</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Early work and then family formation</td>
<td>30 &lt;</td>
<td>&lt; 18</td>
<td>30 &lt;</td>
<td>29.06</td>
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<tr>
<td>2</td>
<td>Work / Education with No family</td>
<td>23.30</td>
<td>21.57</td>
<td>30 &lt;</td>
<td>30 &lt;</td>
</tr>
<tr>
<td>3</td>
<td>Early work and early family</td>
<td>30 &lt;</td>
<td>&lt; 18</td>
<td>20.72</td>
<td>18.67</td>
</tr>
<tr>
<td>4</td>
<td>Conventional pattern (Education /Work and Family)</td>
<td>21.88</td>
<td>21.48</td>
<td>22.71</td>
<td>26.28</td>
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</tbody>
</table>
Table 5. Lifetime Distribution (i.e., cumulative hazard) Probabilities of Transition Events at Ages 18, 24, and 30.

<table>
<thead>
<tr>
<th></th>
<th>Overall population</th>
<th>Early work and then family formation</th>
<th>Work / Education with no family</th>
<th>Early work and early family</th>
<th>Conventional Patterns</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Age 18</td>
<td>Age 24</td>
<td>Age 30</td>
<td>Age 18</td>
<td>Age 24</td>
</tr>
<tr>
<td>Graduate college</td>
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<td>.30</td>
<td>.43</td>
<td>.00</td>
<td>.09</td>
</tr>
<tr>
<td>Full-time work</td>
<td>.39</td>
<td>.89</td>
<td>.95</td>
<td>.55</td>
<td>.92</td>
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<tr>
<td>Marriage</td>
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<td>.33</td>
<td>.52</td>
<td>.02</td>
<td>.29</td>
</tr>
<tr>
<td>Parenthood</td>
<td>.08</td>
<td>.33</td>
<td>.51</td>
<td>.03</td>
<td>.30</td>
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</table>
Table 6. Correlation and Descriptive Statistics among Predictors at Wave 1 (n = 14,224).

<table>
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<tr>
<th></th>
<th>GFE</th>
<th>IP</th>
<th>DEP</th>
<th>PB</th>
<th>DPA</th>
<th>CSA</th>
<th>Age</th>
<th>Female</th>
<th>Black</th>
<th>Hispanic</th>
<th>Asian</th>
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</thead>
<tbody>
<tr>
<td>GFO</td>
<td>-</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>IP</td>
<td>-.19***</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DEP</td>
<td>-.24***</td>
<td>.24***</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PB</td>
<td>-.20***</td>
<td>.11***</td>
<td>.23***</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>DPA</td>
<td>-.24***</td>
<td>.12***</td>
<td>.21***</td>
<td>.32***</td>
<td>-</td>
<td></td>
<td></td>
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<tr>
<td>CSA</td>
<td>-.22***</td>
<td>.10***</td>
<td>.15***</td>
<td>.03*</td>
<td>.09***</td>
<td>-</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Age</td>
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<td>.12***</td>
<td>.09***</td>
<td>.01</td>
<td>.21***</td>
<td>.04**</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
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<td>-.09***</td>
<td>.05***</td>
<td>.14***</td>
<td>-.12**</td>
<td>-.06***</td>
<td>.03**</td>
<td>-.05***</td>
<td>-</td>
<td></td>
<td></td>
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<tr>
<td>Black</td>
<td>-.04***</td>
<td>.02*</td>
<td>.03**</td>
<td>-.01</td>
<td>-.07***</td>
<td>.20***</td>
<td>-.03**</td>
<td>.05***</td>
<td>-</td>
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<tr>
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<td>.01</td>
<td>.07***</td>
<td>.05***</td>
<td>.02*</td>
<td>.15***</td>
<td>.06***</td>
<td>-.01</td>
<td>-.13***</td>
<td>-</td>
<td></td>
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<tr>
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<td>-.03**</td>
<td>.01</td>
<td>.06***</td>
<td>.01</td>
<td>-.03*</td>
<td>-.07***</td>
<td>.04**</td>
<td>-.02</td>
<td>-.09***</td>
<td>.06***</td>
<td>-</td>
</tr>
</tbody>
</table>

Mean (or %) 24.98 8.74 5.39 3.86 .00 1.58 15.61 53.2% 15.8% 13.2% 6.0%

SD 3.29 2.51 3.57 4.49 2.78 1.11 1.72
Minimum 2.00 1.00 .00 .00 -.26 -1.00 5.00 0.00 0.00 0.00 0.00
Maximum 30.00 20.00 24.00 36.00 11.88 4.00 18.00 1.00 1.00 1.00 1.00
Skewness 1.107 0.41 1.07 2.05 .02 .03 .02

Note. GFO= General Future Orientation. IP=Impulsivity. DEP=Depressive symptoms. PB=Problem Behavior. DPA=Deviant Peer Affiliation. SD= Standard Deviation. a = point biserial coefficients (given the correlation between continuous predictors and dichotomous race/ethnicity variables). At Wave 1, 279 (0.2%) individuals who were older than 18 years were excluded from total sample (n=14,503).

* p <.05. ** p <.01 *** p <.001.
Table 7. Hierarchical Multiple Regression Predicting Hazard Functions (compared to Conventional patterns).

<table>
<thead>
<tr>
<th>Reference: Conventional patterns</th>
<th>Early work and early Family</th>
<th>Early work and then family</th>
<th>Work / Education with no family</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Predictor (s) at Wave 1</strong></td>
<td>β [CI] OR</td>
<td>β [CI] OR</td>
<td>β [CI] OR</td>
</tr>
<tr>
<td>Step 1 Cumulative socioeconomic adversity</td>
<td>.53*** [.47, .59]</td>
<td>1.70</td>
<td>.31*** [.26, .35]</td>
</tr>
<tr>
<td><em>Pseudo R²</em></td>
<td>.26</td>
<td>.10</td>
<td>.00</td>
</tr>
<tr>
<td>Step 2 General future orientation</td>
<td>-.06*** [-.07, -.03]</td>
<td>.94</td>
<td>-.08*** [-.09, -.06]</td>
</tr>
<tr>
<td>Impulsivity</td>
<td>.04*** [.02, .07]</td>
<td>1.04</td>
<td>.02* [.01, .04]</td>
</tr>
<tr>
<td>Depressive symptoms</td>
<td>.02* [.01, .05]</td>
<td>1.02</td>
<td>.00 [-.02, .02]</td>
</tr>
<tr>
<td>Problem behavior</td>
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<td>1.03</td>
<td>.03*** [.02, .04]</td>
</tr>
<tr>
<td>Deviant peer affiliation</td>
<td>.07*** [.03, .10]</td>
<td>1.07</td>
<td>.05** [.02, .07]</td>
</tr>
<tr>
<td><em>Pseudo R²</em></td>
<td>.34</td>
<td>.20</td>
<td>.02</td>
</tr>
<tr>
<td>Step 3 Gender</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female (vs. Male)</td>
<td>.33*** [.17, .48]</td>
<td>1.39</td>
<td>-.34*** [-.46, -.23]</td>
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<tr>
<td><em>Races / Ethnicities</em> (vs. White)</td>
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<td></td>
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<tr>
<td>Black</td>
<td>.39*** [.20, .57]</td>
<td>1.47</td>
<td>.26*** [.12, .42]</td>
</tr>
<tr>
<td>Hispanic</td>
<td>.24** [.08, .39]</td>
<td>1.27</td>
<td>.27*** [.11, .45]</td>
</tr>
<tr>
<td>Asian</td>
<td>-.36** [-.61, -.10]</td>
<td>.69</td>
<td>.06 [-.08, .21]</td>
</tr>
<tr>
<td><em>Control</em></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-.09*** [-.13, -.04]</td>
<td>.91</td>
<td>-.07*** [-.11, -.03]</td>
</tr>
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<td><em>Pseudo R²</em></td>
<td>.39</td>
<td>.24</td>
<td>.10</td>
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<tr>
<td><em>Two-way Interaction effects</em></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step 4a Cumulative adversity × Future expectation</td>
<td>.02* [.01, .04]</td>
<td>1.02</td>
<td>.02** [.01, .04]</td>
</tr>
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<td><em>Pseudo R²</em></td>
<td>.40</td>
<td>.25</td>
<td>.10</td>
</tr>
<tr>
<td>Step 4b Cumulative adversity × Impulsivity</td>
<td>-.02* [-.04, -.01]</td>
<td>.98</td>
<td>-.02* [-.04, -.01]</td>
</tr>
<tr>
<td><em>Pseudo R²</em></td>
<td>.40</td>
<td>.25</td>
<td>.11</td>
</tr>
<tr>
<td>Step 4c Cumulative adversity × Depressive symptoms</td>
<td>-.02* [-.04, -.01]</td>
<td>1.02</td>
<td>-.02* [-.04, -.01]</td>
</tr>
<tr>
<td><em>Pseudo R²</em></td>
<td>.40</td>
<td>.24</td>
<td>.10</td>
</tr>
<tr>
<td>Step 4d Cumulative adversity × Problem behavior</td>
<td>-.01** [-.03, -.01]</td>
<td>.99</td>
<td>.00 [-.01, .01]</td>
</tr>
<tr>
<td><em>Pseudo R²</em></td>
<td>.40</td>
<td>.26</td>
<td>.11</td>
</tr>
<tr>
<td>Step 4e Cumulative adversity × Deviant Peer Affiliation</td>
<td>.00 [-.02, .03]</td>
<td>1.00</td>
<td>-.03*** [-.04, -.01]</td>
</tr>
<tr>
<td><em>Pseudo R²</em></td>
<td>.39</td>
<td>.26</td>
<td>.10</td>
</tr>
</tbody>
</table>

Notes. Unstandardized logistic coefficients are shown. CI = Confidence Interval. OR= Odds ratio. All predictors were mean-centered as recommended by Aiken and West (1991). Statistically significant differences are indicated in bold.
* p < .05. ** p < .01. *** p < .001.
Table 8. Hierarchical Multiple Regression Predicting Hazard Functions (compared to Early work and early family).

<table>
<thead>
<tr>
<th>Reference: Early work and early family</th>
<th>Early work and then family</th>
<th>Work / Education with no family</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predictor (s) at Wave 1</td>
<td>β [CI]</td>
<td>OR</td>
</tr>
<tr>
<td>Cumulative socioeconomic adversity</td>
<td>-17*** [-.21, -.13]</td>
<td>.84</td>
</tr>
<tr>
<td></td>
<td>*Pseudo R²: .04</td>
<td></td>
</tr>
<tr>
<td>General future orientation</td>
<td>.01 [-.04, .01]</td>
<td>1.01</td>
</tr>
<tr>
<td>Impulsivity</td>
<td>-.01 [-.03, .01]</td>
<td>.99</td>
</tr>
<tr>
<td>Depressive symptoms</td>
<td>-.03*** [-.04, -.02]</td>
<td>.97</td>
</tr>
<tr>
<td>Problem behavior</td>
<td>.00 [-.01, .02]</td>
<td>1.00</td>
</tr>
<tr>
<td>Deviant peer affiliation</td>
<td>-.02* [-.05, -.01]</td>
<td>.98</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>.05</td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female (vs. Male)</td>
<td>-.72*** [-.82, -.63]</td>
<td>.48</td>
</tr>
<tr>
<td>Races / Ethnicities (vs. White)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>-.05 [-.18, .07]</td>
<td>.95</td>
</tr>
<tr>
<td>Hispanic</td>
<td>.02 [-.14, .18]</td>
<td>1.02</td>
</tr>
<tr>
<td>Asian</td>
<td>.34*** [.16, .53]</td>
<td>1.40</td>
</tr>
<tr>
<td>Control</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>.02 [-.02, .05]</td>
<td>1.02</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>.15</td>
<td></td>
</tr>
<tr>
<td>Two-way Interaction effects</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step 4a Cumulative adversity × Future expectation</td>
<td>.02 [-.01, .04]</td>
<td>1.02</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>.15</td>
<td></td>
</tr>
<tr>
<td>Step 4b Cumulative adversity × Impulsivity</td>
<td>.00 [-.02, .01]</td>
<td>.00</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>.15</td>
<td></td>
</tr>
<tr>
<td>Step 4c Cumulative adversity × Depressive symptoms</td>
<td>.00 [-.01, .01]</td>
<td>1.00</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>.15</td>
<td></td>
</tr>
<tr>
<td>Step 4d Cumulative adversity × Problem behavior</td>
<td>-.01* [-.03, -.01]</td>
<td>1.00</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>.16</td>
<td></td>
</tr>
<tr>
<td>Step 4e Cumulative adversity × Deviant Peer Affiliation</td>
<td>-.03*** [-.04, -.01]</td>
<td>.97</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>.16</td>
<td></td>
</tr>
</tbody>
</table>

Notes. Unstandardized logistic coefficients are shown. CI = Confidence Interval. OR= Odds ratio. All predictors were mean-centered as recommended by Aiken and West (1991). Statistically significant differences are indicated in bold.

*p < .05. **p < .01. ***p < .001.
Table 9. Hierarchical Multiple Regression Predicting Hazard Functions (compared to Early work and then family).

<table>
<thead>
<tr>
<th>Reference: Early work and then family</th>
<th>Work / Education with No family</th>
<th>Predictor(s) at Wave 1</th>
<th>β [CI]</th>
<th>OR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1</td>
<td></td>
<td>Cumulative socioeconomic adversity</td>
<td>-.32*** [-.37, -.28]</td>
<td>.72</td>
</tr>
<tr>
<td></td>
<td></td>
<td>*Pseudo R²</td>
<td>.11</td>
<td></td>
</tr>
<tr>
<td>Step 2</td>
<td></td>
<td>General future orientation</td>
<td>.07*** [.05, .08]</td>
<td>1.07</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Impulsivity</td>
<td>.00 [-.02, .01]</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Depressive symptoms</td>
<td>-.02* [-.04, -.01]</td>
<td>.98</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Problem behavior</td>
<td>.00 [-.01, .01]</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Deviant peer affiliation</td>
<td>-.05*** [-.07, -.03]</td>
<td>.95</td>
</tr>
<tr>
<td></td>
<td></td>
<td>*Pseudo R²</td>
<td>.17</td>
<td></td>
</tr>
<tr>
<td>Step 3</td>
<td></td>
<td>Gender</td>
<td>.12** [.03, .21]</td>
<td>1.12</td>
</tr>
<tr>
<td></td>
<td></td>
<td>*Races / Ethnicities (vs. White)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Black</td>
<td>.25*** [.12, .38]</td>
<td>1.28</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Hispanic</td>
<td>-.05 [-.19, .10]</td>
<td>.95</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Asian</td>
<td>.52** [.17, .86]</td>
<td>1.68</td>
</tr>
<tr>
<td></td>
<td></td>
<td>*Control</td>
<td>-.02 [-.05, .01]</td>
<td>.98</td>
</tr>
<tr>
<td></td>
<td></td>
<td>*Pseudo R²</td>
<td>.20</td>
<td></td>
</tr>
<tr>
<td>Step 4a</td>
<td></td>
<td>Two-way Interaction effects</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cumulative adversity × Future expectation</td>
<td>-.02* [-.04, -.01]</td>
<td>.98</td>
</tr>
<tr>
<td></td>
<td></td>
<td>*Pseudo R²</td>
<td>.21</td>
<td></td>
</tr>
<tr>
<td>Step 4b</td>
<td></td>
<td>Cumulative adversity × Impulsivity</td>
<td>.01 [.00, .02]</td>
<td>1.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td>*Pseudo R²</td>
<td>.20</td>
<td></td>
</tr>
<tr>
<td>Step 4c</td>
<td></td>
<td>Cumulative adversity × Depressive symptoms</td>
<td>.02* [.01, .03]</td>
<td>1.02</td>
</tr>
<tr>
<td></td>
<td></td>
<td>*Pseudo R²</td>
<td>.21</td>
<td></td>
</tr>
<tr>
<td>Step 4d</td>
<td></td>
<td>Cumulative adversity × Problem behavior</td>
<td>-.01 [-.03, .01]</td>
<td>1.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td>*Pseudo R²</td>
<td>.21</td>
<td></td>
</tr>
<tr>
<td>Step 4e</td>
<td></td>
<td>Cumulative adversity × Deviant Peer Affiliation</td>
<td>-.02* [-.04, -.01]</td>
<td>.98</td>
</tr>
<tr>
<td></td>
<td></td>
<td>*Pseudo R²</td>
<td>.21</td>
<td></td>
</tr>
</tbody>
</table>

Notes. Unstandardized logistic coefficients are shown. CI = Confidence Interval. OR= Odds ratio. All predictors were mean-centered as recommended by Aiken and West (1991). Statistically significant differences are indicated in bold.

*p < .05. **p < .01. ***p < .00
Table 10. Descriptive Statistics of All Study Variables (n = 9154).

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean (SD)</th>
<th>Min-Max</th>
<th>Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depressive symptoms (Age 15)</td>
<td>.59 (.48)</td>
<td>.00 – 3.00</td>
<td>1.15</td>
</tr>
<tr>
<td>Depressive symptoms (Age 16)</td>
<td>.62 (.48)</td>
<td>.00 – 3.00</td>
<td>1.09</td>
</tr>
<tr>
<td>Depressive symptoms (Age 17)</td>
<td>.64 (.48)</td>
<td>.00 – 2.88</td>
<td>.97</td>
</tr>
<tr>
<td>Depressive symptoms (Age 18)</td>
<td>.62 (.49)</td>
<td>.00 – 3.00</td>
<td>.99</td>
</tr>
<tr>
<td>Depressive symptoms (Age 30)</td>
<td>.57 (.46)</td>
<td>.00 – 3.00</td>
<td>1.39</td>
</tr>
<tr>
<td>Depressive symptoms (Age 31)</td>
<td>.55 (.45)</td>
<td>.00 – 3.00</td>
<td>1.51</td>
</tr>
<tr>
<td>Depressive symptoms (Age 32)</td>
<td>.55 (.45)</td>
<td>.00 – 2.88</td>
<td>1.44</td>
</tr>
<tr>
<td>Smoking (Age 15)</td>
<td>.93 (.86)</td>
<td>.00 – 3.00</td>
<td>.48</td>
</tr>
<tr>
<td>Smoking (Age 16)</td>
<td>1.06 (.91)</td>
<td>.00 – 3.00</td>
<td>.61</td>
</tr>
<tr>
<td>Smoking (Age 17)</td>
<td>1.14 (.92)</td>
<td>.00 – 3.00</td>
<td>.58</td>
</tr>
<tr>
<td>Smoking (Age 18)</td>
<td>1.28 (.93)</td>
<td>.00 – 3.00</td>
<td>.46</td>
</tr>
<tr>
<td>Smoking (Age 30)</td>
<td>.75 (1.01)</td>
<td>.00 – 3.00</td>
<td>1.45</td>
</tr>
<tr>
<td>Smoking (Age 31)</td>
<td>.69 (.98)</td>
<td>.00 – 3.00</td>
<td>1.58</td>
</tr>
<tr>
<td>Smoking (Age 32)</td>
<td>.66 (.97)</td>
<td>.00 – 3.00</td>
<td>1.78</td>
</tr>
<tr>
<td>Delinquency (Age 15)</td>
<td>.18 (.38)</td>
<td>.00 – 3.00</td>
<td>3.34</td>
</tr>
<tr>
<td>Delinquency (Age 16)</td>
<td>.16 (.36)</td>
<td>.00 – 3.00</td>
<td>3.29</td>
</tr>
<tr>
<td>Delinquency (Age 17)</td>
<td>.15 (.35)</td>
<td>.00 – 3.00</td>
<td>3.35</td>
</tr>
<tr>
<td>Delinquency (Age 18)</td>
<td>.14 (.31)</td>
<td>.00 – 3.00</td>
<td>2.23</td>
</tr>
<tr>
<td>Delinquency (Age 30)</td>
<td>.05 (.20)</td>
<td>.00 – 2.60</td>
<td>3.10</td>
</tr>
<tr>
<td>Delinquency (Age 31)</td>
<td>.04 (.17)</td>
<td>.00 – 3.00</td>
<td>3.98</td>
</tr>
<tr>
<td>Delinquency (Age 32)</td>
<td>.03 (.14)</td>
<td>.00 – 1.60</td>
<td>3.23</td>
</tr>
</tbody>
</table>

Notes. SD=Standard Deviation, Min=Minimum, Max=Maximum.
Table 11. Parameter Estimate of Unconditional Univariate Growth Curve Model of Adolescent Sample (ages 15 to 18).

<table>
<thead>
<tr>
<th></th>
<th>Initial level</th>
<th>Linear Slope level</th>
<th>Factor covariance</th>
<th>Model fit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Variance</td>
<td>Mean</td>
<td>Variance</td>
</tr>
<tr>
<td>Depressive symptoms</td>
<td>.62***</td>
<td>.13***</td>
<td>.01*</td>
<td>.00</td>
</tr>
<tr>
<td>Delinquency</td>
<td>.18***</td>
<td>.16***</td>
<td>-.02*</td>
<td>.08***</td>
</tr>
<tr>
<td>Smoking</td>
<td>1.00***</td>
<td>.45***</td>
<td>.13***</td>
<td>.07***</td>
</tr>
</tbody>
</table>

Note. Unstandardized growth factor coefficients were shown; *$p < .05$. ***$p < .001$. 
Table 12. Identification of Trajectory Classes.

<table>
<thead>
<tr>
<th></th>
<th>LL (df)</th>
<th>BIC</th>
<th>SABIC</th>
<th>Entropy</th>
<th>Trajectory Group size (n)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td><strong>General Psychopathology in adolescence (n = 13,042)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C(2)</td>
<td>-27463.96 (35)</td>
<td>55259.58</td>
<td>55148.36</td>
<td>.98</td>
<td>638</td>
</tr>
<tr>
<td>C(3)</td>
<td>-26331.30 (42)</td>
<td>53079.55</td>
<td>52939.72</td>
<td>.84</td>
<td>748</td>
</tr>
<tr>
<td>C(4)</td>
<td>-25315.30 (49)</td>
<td>51094.92</td>
<td>50939.20</td>
<td>.73</td>
<td>289 (2.2%)</td>
</tr>
<tr>
<td><strong>Psychopathology in adulthood (n = 10,071)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C(2)</td>
<td>-10263.66 (10)</td>
<td>20618.49</td>
<td>20587.71</td>
<td>.97</td>
<td>2575</td>
</tr>
<tr>
<td>C(3)</td>
<td>-6498.64 (14)</td>
<td>13126.33</td>
<td>13081.84</td>
<td>.97</td>
<td>286 (2.8%)</td>
</tr>
<tr>
<td>C(4)</td>
<td>-3911.78 (18)</td>
<td>7989.48</td>
<td>7932.28</td>
<td>.98</td>
<td>54 (0.5%)</td>
</tr>
</tbody>
</table>

Note. LL=Log Likelihood. BIC=Bayesian Information Criteria. SABIC= Sample-size adjusted BIC. Adj.LMR = Adjusted Lo-Mendell-Rubin likelihood ratio test
Table 13. Transition Probabilities of Psychopathology from Adolescence to Young Adulthood (n = 9154).

<table>
<thead>
<tr>
<th>Subgroups</th>
<th>Adolescence (Ages 15 to 18)</th>
<th>Adulthood (Ages 30 to 32)</th>
<th>Row Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(a) Probabilities of psychopathology in adolescence conditional on psychopathology in adulthood</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>High psychopathology</td>
<td>High Substance use</td>
</tr>
<tr>
<td>Moderate and stable</td>
<td>3.6%</td>
<td>59.4%</td>
<td>37.0%</td>
</tr>
<tr>
<td>High and decreasing</td>
<td>11.7%</td>
<td>32.5%</td>
<td>55.8%</td>
</tr>
<tr>
<td>Consistently low</td>
<td>2.0%</td>
<td>15.8%</td>
<td>82.2%</td>
</tr>
<tr>
<td></td>
<td>(b) Joint probabilities of psychopathology in adolescence and adulthood</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moderate and stable</td>
<td>0.6%</td>
<td>10.0%</td>
<td>6.2%</td>
</tr>
<tr>
<td>High and decreasing</td>
<td>1.9%</td>
<td>0.7%</td>
<td>3.3%</td>
</tr>
<tr>
<td>Consistently low</td>
<td>1.6%</td>
<td>12.2%</td>
<td>63.4%</td>
</tr>
<tr>
<td>Column total</td>
<td>2.9%</td>
<td>24.1%</td>
<td>73.0%</td>
</tr>
</tbody>
</table>

Note. Posterior probabilities of all assigned classes were ranged from .73 to .95.
Table 14. Transition Probabilities of Psychopathology by Life Transition Patterns (n = 9154).

<table>
<thead>
<tr>
<th>Subgroups</th>
<th>Adulthood (Ages 30 to 32)</th>
<th>Row Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>High psychopathology</td>
<td>Low psychopathology</td>
</tr>
<tr>
<td></td>
<td>High Substance use</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adolescence (Ages 15 to 18)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(a) Early work and then Family formation (i.e., slow starters)</td>
<td>Moderate and stable</td>
<td>62.6%</td>
</tr>
<tr>
<td></td>
<td>High and decreasing</td>
<td>37.0%</td>
</tr>
<tr>
<td></td>
<td>Consistently low</td>
<td>18.8%</td>
</tr>
<tr>
<td>Adolescence (Ages 15 to 18)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(b) Work / education with no family formation</td>
<td>Moderate and stable</td>
<td>40.2%</td>
</tr>
<tr>
<td></td>
<td>High and decreasing</td>
<td>22.7%</td>
</tr>
<tr>
<td></td>
<td>Consistently low</td>
<td>11.3%</td>
</tr>
<tr>
<td>Adolescence (Ages 15 to 18)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(c) Early work and early family formation (i.e., precocious maturity)</td>
<td>Moderate and stable</td>
<td>66.7%</td>
</tr>
<tr>
<td></td>
<td>High and decreasing</td>
<td>26.2%</td>
</tr>
<tr>
<td></td>
<td>Consistently low</td>
<td>21.4%</td>
</tr>
<tr>
<td>Adolescence (Ages 15 to 18)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(d) Conventional pattern (school-to-work transition in early twenties and family formation)</td>
<td>Moderate and stable</td>
<td>45.3%</td>
</tr>
<tr>
<td></td>
<td>High and decreasing</td>
<td>13.6%</td>
</tr>
<tr>
<td></td>
<td>Consistently low</td>
<td>6.1%</td>
</tr>
</tbody>
</table>
Adolescence Period (Ages: 15-18)

Developmental patterns of Psychopathology
(Depressive symptoms, Delinquency, and Smoking)

Transition Period (Ages: 18-30)

Transition Patterns

Life Transition Patterns
(College graduation, Full-time employment, Marriage, and Parenthood)

Adulthood Period (Ages: 30-32)

Average Patterns of Psychopathology
(Depressive symptoms, Delinquency, and Smoking)

Early influential factors
- Individual characteristics
- Contextual adversities
- Gender and Races/Ethnicities

Figure 1. Overall Conceptual Model.
Figure 2. Conceptual Model of the First Study.
Repeated binary indicators for hazard function of single event

Panel a. *Univariate* discrete-survival time growth mixture model (GMM)

Panel b. *Univariate* discrete-survival longitudinal latent class model (LLCM)

Figure 3. Comparison between Growth Mixture Model (GMM) and Longitudinal Latent Class Model (LLCM).
Figure 4. Conditional *Multivariate* Discrete-Time Survival Mixture (MDTSM) Model (A statistical model of the current study).
Figure 5. Sample Observed Probabilities.
Figure 6. Moderating Effects of Cumulative Socioeconomic Adversity on the Association between Predictors and Class Membership (Reference: Conventional transition pattern).

Note. Unstandardized coefficients are shown. All threshold (intercept) values are significant at $p < .01$. CP = Crossover points. SE = Standard error. For estimating simple slope, high and low moderator group is created based on 1 SD above and below the mean score (Preacher, Curran, & Bauer, 2006). Mean centered values are shown in parentheses.

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

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Figure 7. Moderating Effects of Cumulative Socioeconomic Adversity on the Association between Predictors and Class Membership (Reference: Early work and early family pattern).

Note. Unstandardized coefficients are shown. All threshold (intercept) values are significant at $p < .01$. CP = Crossover point. SE = Standard error. For estimating simple slope, high and low moderator group is created based on 1 SD above and below the mean score (Preacher, Curran, & Bauer, 2006). Mean centered values are shown in parentheses.

*** $p < .001$. 
Figure 8. Moderating Effects of Cumulative Socioeconomic Adversity on the Association between Predictors and Class Membership (Reference: Early work and then family pattern).

Note. Unstandardized coefficients are shown. All threshold (intercept) values are significant at $p < .01$. CP = Crossover point. SE= Standard error. For estimating simple slope, high and low moderator group is created based on 1 SD above and below the mean score (Preacher, Curran, & Bauer, 2006). Mean centered values are shown in parentheses.

** $p < .01$. *** $p < .001$. 
Figure 9. Conceptual Model of the Second Study. 
Figure 10. Second-order Growth Mixture Model of Factor-of-Curves Model (SOGMM-FCM).
Note. I=Intercept. S= Slope. C= Class. DEP=Depressive symptoms. DLQ=Delinquency. SMK=Smoking. GP=General Psychopathology
Figure 11. Estimated Three Classes’ Mean Trajectories of General Psychopathology in Adolescence (ages 15 to 18).

Notes. Unstandardized growth coefficients (b_0 and b_1 for intercept and slope, respectively) were shown. *p < .05, ***p < .001.
Figure 12. Confirmatory Factor Structure of Psychopathology in Adulthood (ages 30 to 32).

Notes. Standardized loading coefficients were shown. Depressive symptoms was used as a marker variable. $\chi^2$(df) = .00(0); CFI / TLI = 1.00 / 1.00; RMSEA = .00.

***p<.001.
Figure 13. Estimated Mean of Three Classes of Psychopathology in Adulthood (ages 30 to 32).

Notes. Unstandardized coefficients were shown.