A Person-Centered Analysis of Risk Factors that Compromise Wellbeing in Emerging Adulthood

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ABSTRACT

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Sarah Newcomb-Anjo

The transition to adulthood is marked by potential for both enhanced wellbeing and problematic outcomes, such as mental health problems. The purpose of this study was to identify profiles of emerging adults with different risk factor experiences, and to examine whether these profiles were differentially related to mental health and academic wellbeing. Undergraduate emerging adults (N = 903, 82% female), aged 18-25 years (M = 21.14, SD = 1.75), completed a series of questionnaires about childhood, current contextual, and dispositional risk factors, mental health, and academic variables. Results from a cross-sectional latent profile analysis identified four distinct risk profiles: *Low Risk* (76%), *Low Social Support Risk* (4%), *Financial Risk* (11%), and *Multiple Risk* (8%). Overall, individuals within the *Multiple Risk* group fared the worst across the majority of wellbeing outcomes. However, individuals within the *Financial Risk* and *Multiple Risk* were comparable to each other in many instances, displaying more depressive symptoms, lower self-esteem, and lower life satisfaction relative to those in the *Low Risk* and *Low Social Support Risk* profiles. All risk profiles were comparable on levels of positive affect and academic performance, and those within the three risk-prone groups reported more academic stress relative to the *Low Risk* profile. Implications for targeted interventions are discussed.

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A Person-Centered Analysis of Risk Factors that Compromise Wellbeing in Emerging Adulthood

The period of the life course between adolescence and adulthood, *emerging adulthood* (EA), is regarded as a socially, physically, and neurologically unique developmental life stage (Arnett, 2000). Understanding characteristics of healthy psychosocial development in EA has been highlighted as a fundamental task for developmental science (O'Connor et al., 2011). Like other transitions across the life course, EA is a sensitive time for engaging opportunities, but also experiencing threats for wellbeing (Mortimer & Shanahan, 2003). Scholars have noted that the uncertainty, increased responsibility, and demands on self-direction that typify EA can contribute to declines in subjective wellbeing and mental health (Hendry & Kloep, 2007; Schulenberg, Sameroff, & Cicchetti, 2004). Indeed, some studies have shown that mental health problems peak during the transition to adulthood (Akhtar-Danesh & Landeen, 2007; Eisenberg, Golberstein, & Gollust, 2007; Kessler, Chiu, Demler, & Walters, 2005; Rohde, Lewinsohn, Klein, Seeley, & Gau, 2013), and that prevalence rates for psychiatric diagnoses in EA reach as high as approximately 50% (Blanco et al., 2008). However, EA has conversely been described as a window of opportunity for positive change (Masten Obradović, & Burt, 2006; Arnett, 2007) and some studies have shown that average levels of mental health tend to improve in EA (Galambos, Barker, & Krahn, 2006; Schulenberg & Zarret, 2006; Tanner et al., 2007). Clearly, wellbeing in EA is a heterogeneous phenomenon (Shanahan, 2000; Schulenberg & Zarret, 2006). Thus, efforts are needed to determine factors that promote versus attenuate wellbeing during this life period.

With increasing numbers of emerging adults pursuing post-secondary education (Arnett, 2004; Statistics Canada, 2010), understanding factors that influence wellbeing specifically in university students is an important goal as well. For example, with this transition come shifts in vocational expectations, social relationships, and financial constraints, causing students to report high levels of stress (Aquilino, 2006; Arnett, 2004; Laursen & Collins, 2006; Monk, 2004; Roberts & Zelenyanksi, 2002). Indeed, a recent large survey of college and university students showed that approximately 50% of students reported their academic demands to be very difficult to handle (American College Health Association, 2015) and many university students report high levels of anxiety and depression (Blanco et al., 2008; Ibrahim, Kelly, Adams, & Glazebrook, 2013; Pryor, Hurtado, DeAngelo, Palucki Blake, & Tran, 2010). Furthermore, understanding factors that promote or hinder emerging adults' mental and academic wellbeing is important because both are highly predictive of later life mental health, job obtainment, postgraduate studies, and financial security (French, Homer, Popovici, & Robins, 2015; Howard, Galambos, & Krahn, 2010; Ingram & Gallagher, 2010; Masten et al., 2006; Stoolmiller, Kim, & Capaldi, 2005).

Predictors of Wellbeing in EA: Risk and Protective Factors

In an attempt to understand predictors of wellbeing in EA, many studies have turned to the examination of risk (and protective) factors. Risk factors are defined as antecedent characteristics, experiences, or events that, if present, are associated with an increased probability of a particular deleterious outcome, such as mental health problems (Kraemer et al., 1997)[1]. Risk factors can be derived from diverse domains (e.g., biological, social, psychological) and a variety of risk factors have been identified in the prediction of wellbeing in EA (e.g., Schilling, Aseltine, & Gore, 2008). However, despite the empirical fact that many risk factors co-occur and interact, few studies have examined multiple risk factors in conjunction (Cicchetti & Rogosch, 2002; Sameroff, 1993). Yet, the multifaceted nature of wellbeing in EA most likely reflects multiple influences from multiple domains across the life course (Lerner, 2002). Accordingly, a thorough assessment of risk factors that relate, contribute to, or compromise wellbeing in EA warrants systematic modeling of risk factors across multiple domains. The risk research on risk factors predicting wellbeing in EA can be summarized into three domains: childhood risks, current contextual risks, and dispositional risks.

Childhood risk factors. Informed by the life course perspective, the influence of stressors in childhood on EA outcomes has been well established (Schilling et al., 2008). In particular, the link between childhood socioeconomic status (SES) and later mental health and academic attainment has been extensively supported (McLoyd, Kaplan,

[1] Conversely, protective factors refer to antecedent conditions that are associated with a decrease in the likelihood of undesirable outcomes, or with an increase in positive outcomes (Rutter, 1979; Kazdin, Kraemer, Kessler, Kupfer, & Offord, 1997). Because risk-factor research as an approach encompasses both risk and protective factors, the present paper addresses the contribution of both categories, while referring to them solely as risk factors for simplicity.

Purtell, & Huston, 2011; Wickrama, Noh, & Elder, 2009; Yoshikawa, Aber, & Beardslee, 2012). For example, emerging adults coming from low SES families are more likely to be employed part-time as opposed to those coming from high SES families, which in turn is related to higher perceived stress and lower academic achievement (Lee & Staff, 2007). Similarly, research has shown that university students who indicate that they grew up in poor families are substantially more likely (odd ratios above 3) to screen positive for depression or anxiety disorder and to report suicidal thoughts (Eisenberg et al., 2007).

Adverse childhood *events*, such as the experience of abuse are also strongly predictive of wellbeing in EA as well (e.g., McMahon, 2014). While all forms of abuse (e.g., physical, sexual, emotional) threaten emerging adults' wellbeing, research suggests that verbal or emotional abuse is the most salient in compromising wellbeing outcomes (Alloy et al., 2001). In particular, those who report the presence of verbal or emotional abuse in childhood tend to have a greater presence of later depression (Gibb, Benas, Crossett & Uhrlass, 2007; Harkness & Lumley, 2008), anxiety (Wright, Crawford, & Del Castillo, 2009), and mental health diagnoses (Wekerle et al., 2001). Likewise, for many, incidents of maltreatment in childhood have longstanding impacts on later grade point average and school absenteeism rates (Leiter, 2007; Shonck & Cicchetti, 2001), and threaten emerging adults' perceived academic competence (Clarke, 2015).

Current situational risk factors. Beyond risk factors that have been studied in childhood, it is important to also consider risk experiences that occur later in life, to fully grasp current functioning (Curtis & Cicchetti, 2003; Schulenberg et al., 2004; Schulenberg, Maggs, & O'Malley, 2003). This is especially pertinent in EA, as EA affords the potential for resilience, whereby the negative effects of previous risk factors can be ameliorated or reversed by new experiences (Cichetti & Rogosch 2002; Masten et al., 2004; Rutter, 2006). Similarly, because EA is a qualitatively unique life stage, the consideration of developmentally salient risk factors is warranted (Roisman, Masten, Coatsworth, & Tellegen, 2004).

Among contextual risk factors in EA, perceived social support is a central resource for wellbeing (Arnett, 2004; Murphy, Blustein, Bohlig & Platt, 2010; O'Connor et al., 2010). Indeed, studies have shown that increased social support protects against depression in EA (Pettit, Roberts, Lewinsohn, Seeley, & Yaroslavsky, 2011), and supports positive trajectories of wellbeing in young adults (Schulenberg, Bryant, & O'Malley, 2004). In addition, university students who reported less social support struggle more with the transition to college (Murphy et al., 2010). In considering different sources of social support, the parental bond, in addition to peer and romantic connections, have all been identified as vital for wellbeing in EA (van Wel, ter Bogt, & Raaijmakers, 2002).

Beyond childhood indicators of SES, a glimpse into emerging adults' current financial status is important as well, as EA is characterized by increases in self-sufficiency and financial independence (Arnett, 2004; Tanner & Arnett, 2011). Further, an individual's familial finances have been contrasted with temporally distinct EA financial issues in their relation to wellbeing outcomes (Terriquez & Guarantz, 2014). For example, students' personal income, irrespective of their parental income, has been independently related to their odds of having a psychiatric disorder (Blanco et al., 2008). Moreover, current financial stress has also been related to decreases in student motivation and persistence in academic work (Jung, 2013).

In addition to social support and current financial contextual risks, the presence of recent negative life events has been related to wellbeing in EA as well (Hammen, 2003). For example, the recent experience of negative life events such as death of a family member or the loss of employment are related to elevated depression rates in EA (Rao, Hammen, Ortiz, Chen, & Poland, 2008). Similarly, among college attending emerging adults, having a higher number of stressful life events in the past 12 months is significantly related to having a psychiatric disorder (Blanco et al., 2008) and deters students' academic performance (De Meuse, 1985).

Dispositional risk factors. Consistent with the transactional model of development (Sameroff & Chandler, 1975), substantial research has shown that individuals' own characteristics affect their wellbeing outcomes as well. Further, prevention science has highlighted the importance of considering potentially *malleable* risk factors in EA, such as dispositions, to better guide intervention efforts (Luecken & Gress, 2010). Dispositional risk factors linked to wellbeing in EA include neuroticism, dispositional optimism, and negative cognitive style. The personality trait of neuroticism, the tendency to experience negative emotional states, has been well established as a concomitant of various mental health problems (Jang, Wolf, & Larstone, 2006). Similarly, dispositional optimism, the general expectation of positive outcomes, has been consistently inversely related to mental health problems (Alarcon, Bowling, & Khazon, 2013; Scheier, Carver, & Bridges, 1994). For example, emerging adult university students that are more optimistic report less stress and more adaptive goal regulation capacities (Rasmussen, Wrosch, Scheier, & Carver, 2006). Theoretically similar to neuroticism and optimism is negative cognitive style, the attributions that one makes about the causes, consequences and self-worth implications of negative life events (Abramson, Metalsky, & Alloy, 1989). Negative cognitive style is regarded as a precursor to psychopathology and influences perceived stress and coping with academic demands (Alloy et al., 2000; Misra & Castillo, 2004).

Variable-Centered Conceptualizations of Risk Factors

While much research has established the role of childhood, current situational, and dispositional risk factors in EA wellbeing, to date, the majority of developmental psychopathology and risk factor research has used variable-centered methods (Burchinal, Roberts, Hooper, & Zeisel, 2000; Magnusson & Bergman, 1988). Such methods include single variable, two-way interactive, and cumulative risk approaches, which seek to examine shared variance between variables and identify processes common to all members of a group (Magnusson, 2003; Muthén & Muthén, 2000). While informative, these methods assume that there are no unidentified subgroups within the population, which may limit their contribution to real-life applications (Laursen & Hoff, 2006). Further, approaches such as single variable and two-way interactive methods include only a select number of risk factors in the analysis, thereby limiting their insight into full human functioning (Magnusson, 2003).

When multiple risk factors are considered simultaneously in an analysis, they are traditionally operationalized using cumulative risk indices (Caprara & Rutter, 1995; Sameroff, Seifer, Barocas, Zax, & Greenspan, 1987). In this approach, variables representing risk factors are summed and used as predictors of psychopathology, with increasing risks often being associated with increasingly deleterious outcomes (e.g., Appleyard, Egeland, van Dulmen, & Sroufe, 2005; Sameroff, 2000a). However, this method fails to adequately capture the different risk backgrounds of individuals and regards the risk factors as equally weighted and interchangeable in meaning (Deater-Deckard, Dodge, Bates, & Pettit, 1998). Similarly, empirical investigations have shown that the effects of high cumulative risk indices on outcomes may be confounded by the experience of more severe risks (Schilling et al., 2008). Thus, while cumulative risk approaches have undoubtedly contributed to our understanding of human functioning, they may overlook how certain risk factors interact, or how their effects may vary across different subpopulations.

Person-Centered Conceptualizations of Risk Factors

Because of the limitations inherent to variable-centered approaches, several scholars have noted the importance of *person*-centered methods, particularly in studying complex phenomena such as psychopathology (Magnusson & Berman, 1988). Person-centered analyses aim to identify groups or types of individuals based on their parallel endorsements of variables (Magnusson, 2003; Muthén & Muthén, 2000). Thus, the unit of analysis for these methods is the *individual*, rather than the variable, emphasizing diversity rather than the average trajectory (Magnusson, 2003). A person-centered approach to studying risk factors acknowledges the processes of *multifinality*, whereby the contributions of risk factors to development may vary between individuals (Cicchetti & Rogosch, 1996; Sameroff, 2000b). Such methods are also particularly important in understanding psychopathology and wellbeing in emerging adulthood, as they allow for and explain heterogeneity (Arnett, 2000; Luecken & Gress, 2010).

Finite mixture modeling (McLachlan & Peel, 2005) is a person-centered approach that assumes the existence of underlying subgroups, or mixtures within a population. With mixture modeling, one can model interactions between multiple risk factors within individuals, thereby identifying a set of homogenous and mutually exclusive risk subgroups. These subgroups can then be related to distal outcomes, to understand how the subgroups may differ in their prediction of various outcomes. Also referred to as latent class or profile models, mixture modeling has been used to model multiple risk factors and examine relationships between profiles of risk and diverse childhood and adolescent outcomes (e.g., Coffman, Patrick, Palen, Rhoades, & Ventura, 2007; Lanza, Rhoades, Nix, Greenberg, & the Conduct Problems Prevention Research Group, 2010;

Rhoades, Greenberg, Lanza, & Blair, 2011; Syversten, Cleveland, Gayles, Tibbits, & Faulk, 2010).

The Current Study

This study aims to provide insight into the relationship between risk factors and wellbeing during the transition to adulthood. Specifically, the objectives of this study were to (a) identify distinct profiles of emerging adults based on a combination of childhood, current contextual, and individual dispositional risk factors, and (b) to examine whether these profiles of risk differentially relate to emerging adults' mental health and academic wellbeing. Given the diversity of pathways observed in emerging adulthood (Arnett, 2000), we hypothesized that person-centered analyses would reveal heterogeneity in emerging adults' risk factor experiences. Because no prior studies have examined the interrelations among childhood, current contextual and dispositional risk factors in EA, we made no a priori hypotheses regarding the number of profiles that would emerge. We did, however, hypothesize that at least one profile would emerge as a low risk group, having fewer risk factors and higher levels of adaptive dispositions and social support, and that other profiles would have varying degrees of risk. We also hypothesized that differential risk factor clusters would be related to various mental health and academic outcomes in meaningful ways. In particular, we expected emerging adults within the low risk profile would report better mental health and academic outcomes than those who experienced more risk factors. This research hopes to expand our thinking beyond traditional conceptualizations of risk factors in relation to wellbeing in EA and galvanize new approaches for responding to the difficulties individuals face during this life period.

Method

Participants and Procedures

Participants were 903 emerging adult university students (159 male and 744 female) attending Concordia University. Participants ranged in age from 18 to 25 years (M = 21.14, SD = 1.75) and predominately identified themselves as White (74.4% White, 12.4% Asian, 5.5% Black, 6.6% another racial group). Participants were completing their first university undergraduate degree at the time of data collection and were evenly distributed across the first three years of study (27.3% first year, 30% second year, 26.6%

third year, and 17% enrolled in their fourth year or beyond). Participants also reported a range of family incomes, with the median annual family income in the $50,000.00 to $75,000.00 CAD range.

Participants were recruited during three academic years, from December 2011 through April 2015, at student events, by flyers posted on campus and through the online psychology participant pool system. Individuals who indicated their interest by providing their information on sign-up sheets or by contacting the research team directly (37.1% of the sample) were sent an email that described the study and were provided a link to an online survey. Participants who expressed interest in the study through the online participant pool system (62.9% of participants) were provided with a link to an online survey. Participants were reimbursed for their participation with either $20 cash, a $20 gift card for a popular retailer, or a course credit. Additionally, draws were held or $100 gift cards to the university book store. The final sample for the present study included those who had complete data on at least one of the risk indicators used in the analysis.

Measures

Childhood risk variables.

Childhood subjective socioeconomic status. Childhood subjective socioeconomic status (SES) was assessed by a single question adapted from the *MacArthur Scale of Subjective Social Status* (Goodman et al., 2001). This version of the question asks participants to indicate their perceived family status while growing up, relative to other families on a metaphorical status ladder. Scores ranged from 1 "worst off" to 11 "best off".

Childhood verbal abuse. Childhood verbal abuse was assessed by a single item adapted from the *Adverse Childhood Experiences study* (2009). This item asked how frequently participants experienced "someone swearing threatening, insulting or putting them down" while growing up. Responses were scored on a 5-point Likert scale (0 = *never*, 5 = *very often*).

Current situational risk variables.

Current financial strain. Current financial strain was operationalized in the current study as participants' inability to afford certain life essentials. Questions were adapted from Pearlin and Schooler (1978) and included a list of essentials (clothing, food, transportation, leisure activities, school supplies, medical/health supplies and/or bills) that participants were unable to afford. Response options indicated the frequency of strain, ranging from 0 = “never” (never unable to afford), 1= “time to time”, and 2 = “every month” (unable to afford every month). Mean scores were calculated such that higher scores indicated greater financial distress. The inter-item reliability for the current sample was good (*a* = .88).

Recent negative life events. Negative life events occurring in the last 12 months was measured using an adapted version of the *PERI Life Events Scale* (Dohrenwend, Askenasy, Krasnoff, & Dohrenwend, 1978). Items measured the occurrence of nine negative life events within the last year, specific to the participant (loss of employment, problem at work, financial problem, legal problem, living arrangement problem, death of a friend or family member, major physical illness/injury, alcohol or drug problem and/or mental health problem). Participants indicated whether they had experienced these events in the last year. If endorsed, participants received a score of “1” for that time and then the nine dichotomously scored items were summed, such that higher scores indicated having experienced more negative life events in the previous 12 months.

Perceived social support. Perceived social support was assessed using the 12-item *Multidimensional Scale of Perceived Social Support* (MSPSS; Zimet, Dahlem, Zimet, & Farley, 1988). The MSPSS is a self-report measure used to assess perceived social support from friends, family and a special person (e.g., “I get the emotional help and support I need from my family”). Participants were asked to indicate their level of agreement with each statement based on 7-point Likert scale (1= *Very strongly disagree*, 7 = *Very strongly agree*).). Mean scores were calculated such that higher scores indicated greater perceived social support. The inter-item reliability for the current sample was high (*a* = .94).

Dispositional risk variables.

Neuroticism. Neuroticism was assessed using the neuroticism subscale from the *Mini-International Personality Item Pool* (Donellan, Oswald, Baird, & Lucas, 2006). This scale is comprised of 4 items (e.g., “I get upset easily”) and participants indicate their level of agreement with each statement based on a 5-point Likert scale (1 = *Very inaccurate*, 5 = *Very accurate*).). Mean scores were calculated such that higher scores indicated greater neuroticism. The inter-item reliability for the current sample was acceptable (*a* = .64).

Negative cognitive style. Negative cognitive style was assessed using an adapted version of the *Cognitive Style Questionnaire*, *short form* (Meins et al., 2012), a 9-item self-report measure that assesses cognitive thinking responses to difficult scenarios. Participants were asked to choose one of four scenarios that would be the most upsetting to them (a work, social, romantic or academic option) and then rate their level of agreement with each response to that event (e.g., "I would think it means that there is something wrong with me as a person") based on a 5-point Likert scale (1 = *Strongly disagree*, 5 = *Strongly agree*). Mean scores were calculated such that higher values indicated a more negative/maladaptive cognitive styles. Inter-item reliability for the current sample was good (*a* = .87).

Optimism. Dispositional optimism was assessed using the *Life Orientation Test-Revised* (LOT-R; Scheier et al., 1994). The LOT-R is a 10-item self-report measure used to assess participants' global outlook on life, with higher values indicative of more optimistic outlooks (e.g., "In uncertain times, I usually expect the best"). Participants were asked to indicate their level of agreement with each statement based on a 5-point Likert scale (0 = *Strongly disagree*, 5 = *Strongly agree*). Mean scores were calculated such that higher values indicated greater optimism. Inter-item reliability for the current sample was acceptable (*a* = .77).

Mental health outcome variables.

***Depressive symptoms*.** Depressive symptoms were assessed using the *Centre for Epidemiologic Studies Depressions Scale* (CESD; Radloff, 1977). The CESD is a 20-item self-report measure used to assess depressive symptoms within the last week (e.g., "I thought my life had been a failure"). Participants were asked to indicate the frequency of the feelings and behaviours based on a 4-point Likert scale [0 = *Rarely (less than 1 day)*, 3 = *Most of the time (5-7 days)*]. Mean scores were calculated such that higher values indicated greater depressive symptomatology. Inter-item reliability for the current sample was good (*a* = .90).

Anxiety. Anxiety was assessed using the anxiety subscale of the *Hospital Anxiety and Depression Scale* (HADS; Zigmond & Snaith, 1983). The anxiety subscale of the

HADS is a 7-item self-report measure that assesses general anxiety symptoms (e.g., “I get sudden feelings of panic”). Participants were asked to indicate the frequency of the symptoms based on a 4-point Likert scale (0 = *Not at all*, 3 = *Very often*). Mean scores were calculated such that higher values indicated greater anxiety. Inter-item reliability for the current sample was acceptable (*a* = .80).

Self-esteem. Self-esteem was assessed using the Rosenberg Self-Esteem scale (RSE; Rosenberg, 1965), a 10-item self-report measure. Participants were asked to indicate how strongly they agreed with the statements (e.g., “I feel that I have a number of good qualities”), based on a 4-point Likert scale (0 = *Strongly disagree*, 3 = *Strongly agree*). Mean scores were calculated such that higher values indicated greater self-esteem. Inter-item reliability for the current sample was good (*a* = .89).

***Life satisfaction*.** General life satisfaction was assessed using the *Satisfaction with Life Scale* (SWLS; Diener, Emmons, Larsen, & Griffin, 1985), a 5-item self-report measure. Participants were asked to indicate how strongly they agree with the statements (e.g., “If I could live my life over, I would change almost nothing”), based on a 7-point Likert scale (1 = *Strongly Disagree*; 7 = *Strongly Agree*). Mean scores were calculated such that higher values indicated greater life satisfaction. Inter-item reliability for the current sample was good (*a* = .88).

Positive affect. Positive affect was assessed using the positive affect subscale of the *Positive and Negative Affect Schedule* (PANAS; Watson, Clark, & Tellegen, 1988). The positive affect subscale of the PANAS is a 10-item self-report measure used to assess the extent to which an individual experiences pleasurable engagement with the environment. Participants were asked to indicate the frequency of the feelings (e.g., “interested”) over the past week on a 5-point Likert scale (1 = *Very slightly or Not at All*, 5 = *Extremely*). Mean scores were calculated such that higher values indicated greater positive affect in the previous week. Inter-item reliability for the current sample was good (*a* = .88).

***Negative affect*.** Negative affect was assessed using the negative affect subscale of the *Positive and Negative Affect Schedule (*PANAS; Watson et al., 1988). The negative affect subscale of the PANAS is a 10-item self-report measure used to assess the extent to which an individual experiences distress and displeasure in engaging with the environment. Participants were asked to indicate the frequency of the feelings (e.g., "hostile") over the past week on a 5-point Likert scale (1 = *Very slightly or Not at All*, 5 = *Extremely*). Mean scores were calculated such that higher values indicated greater negative affect in the previous week. Inter-item reliability for the current sample was good (*a* = .84).

Academic wellbeing outcome variables.

Subjective academic performance. Participants' subjective assessment of their own academic performance was assessed using a single item. This item asked in what range do participants' grades "tend to fall". Responses were scored on an 8-point scale, with a higher score indicative of higher grades (1 = *Ds and failures*, 8 = *As*).

Subjective academic stress. Subjective academic stress was measured using an adapted version of the *Perceived Stress Scale* (PSS; Cohen, Kamarck, & Mermelstein, 1983). Items measured the extent to which participants felt stressed and in control of their academic demands (e.g., "How often have you felt confident in your ability to handle your academic work?"). Participants were asked to indicate the frequency of the feelings on a 5-point Likert scale (0 = *Never*, 4 = *Very Often*). Mean scores were calculated such that higher values indicated greater perceived academic stress. Inter-item reliability for the current sample was good (*a* = .81).

Results

Descriptive Statistics

Data screening was performed according to the guidelines described by Tabachnick and Fidell (2013) using IBM SPSS Statistics version 22. A small amount (< 2%) of univariate outliers were present on some of the risk variables used in the analysis. However, given that this is to be expected with large sample sizes (Tabachnick & Fidell, 2013) and that outliers may be meaningful to risk research, the cases were not changed or deleted. Violations of normality (e.g., skew, kurtosis) were also present across some of the variables used in the analysis. However, in mixture modeling, while the population is assumed to be a mixture of two (or more) normal distributions, the population distribution *itself* need not be normal (Pastor, Barron, Miller, & Davis, 2006). Thus, as recommended by Bauer & Curran (2003), we assume this nonnormality reflects a mixture of unobserved groups (e.g., "high risk" students among a larger group of relatively “low risk” students), and chose not to transform or remove these cases, to provide a more accurate picture of the heterogeneity that may exist in the sample. This assumption of informative nonnormal data has also been applied in other substantive domains of risk research, such as drug and alcohol use and anti-social behaviour literature (e.g., Chassin, Pitts, & Provost, 2002; Muthén & Muthén, 2000), where mixture models have been applied with high frequency. Descriptive statistics for all study variables are presented in Table 1.

Missing Data

Missing data in the form of variable non-response was present across some of the variables in the analysis. Univariate t-tests comparing participants with and without missing data on a range of variables (e.g., all variables included in the analyses, other indicators of wellbeing, and demographic variables) were conducted to assess the mechanism of missing data in the present sample (Rubin, 1976). Results indicated that data missingness was likely Missing At Random (MAR) given that the probability of missing data was related to other study variables but not to the missing data values themselves (Enders, 2010). Specifically, participants with missing data were more likely to self-identify as Black than White, Asian or another racial identity, to be in their first year of their degree as opposed to later years, to be recruited from flyers and student events as opposed to recruited on the psychology participant pool, to have completed the survey later in the semester, or to have a mother with a lower level of education. Patterns of nonresponse suggested that participant fatigue was the most likely cause of missing data.

All models were estimated in Mplus version 7 (Muthén & Muthén, 1998-2012), under missing data theory using all available data and robust Full Information Maximum Likelihood Estimation (FIML). This strategy for handling missing data is a contemporary method of modeling with missing data that makes use of all available data points (Little, Jorgensen, Lang, & Moore, 2013) This method also accounts for non-normally distributed data by adjusting standard errors and scaling chi square statistics, thereby making it especially suitable for risk research, whereby the data are often non-normally distributed (Enders, 2001; Enders & Bandalos, 2001; Berlin, Williams, & Parra, 2013). Alternative modern approaches to handling missing data were considered but not chosen because they are not available within a mixture modeling framework (e.g., using auxiliary variables to predict missingness with FIML) or would prevent the availability of indices to determine the optimal number of profiles (e.g., mixture model comparison indices are not available within multiple imputation techniques).

Statistical Analyses

A Latent Profile Analysis (LPA), a cross-sectional type of finite mixture modeling that utilizes continuous profile indicators, was conducted in Mplus version 7.0. Specifically, the LPA was applied to determine whether there was heterogeneity in the current sample based on the eight risk factors assessed in the current study: childhood verbal abuse, childhood subjective SES, current financial strain, recent negative life events, perceived social support, neuroticism, optimism, and negative cognitive style. One-, two-, three-, four-, and five-profile models were estimated and compared across parameter estimates, fit indices and model information criteria. Profiles were then related to the eight wellbeing outcomes assessed in the current study: depressive symptoms, anxiety, life satisfaction, self-esteem, positive affect, negative affect, subjective academic performance, and subjective academic stress. Specifically, the *probability* of being in each profile was related to the outcome variables of interest. However, because there is some degree of uncertainty in profile membership, it would be inappropriate to simply assign individuals to the latent profiles based on their maximum posterior probability (e.g., Nagin, 2005), as this method ignores any uncertainty in each individual's true profile membership. Instead, a multiple pseudo-class draws approach (Bandeen-Roche, Miglioretti, Zeger, & Rathouz, 1997; Wang, Brown, & Bandeen-Roche, 2005) was used. This approach mimics the maximum probability assignment method but accounts for uncertainty in profile membership. Specifically, the outcome variable is related to the profile membership multiple (typically 20) times. Results are then combined across the multiple draws using an approach similar to multiple imputation of missing data (Rubin, 1987).

While some methodologists recommend including outcome variables in the first profile enumeration step, given the number of variables in the present study and our desire for the profile formation to not be impacted by the outcome variables, it was not practical to perform this type of "one-step" model (Vermunt, 2010). Further, the "two step" approach (using pseudo-class draws) used here is in line with the theoretical cause-effect pairing of our research question (Petras & Masyn, 2009), and avoids potential bias in the profile enumeration stage, as demonstrated recently in an empirical study (Diallo, Morin, & Lu, accepted).

Latent Profile Analysis Profile Enumeration

While there are is no single method for comparing models with differing numbers of profiles that is widely accepted (Muthén & Asparouhov, 2006), we chose to compare solutions across six different indices available. First, the scaled log-likelihood (LL) value (correcting for maximum likelihood estimation) was examined, with higher values indicating better fit than lower values. Second, the sample-adjusted Bayesian Information Criterion (BIC; Schwarz, 1978) was used to compare models with different numbers of profiles, with lower values indicating better fit. Often, the BIC will continue to decrease with increasing numbers of latent profiles, but one can use an "elbow" plot to discern where the drop in value becomes less pronounced (Petras & Masyn, 2009; Masyn, 2013). The profile amount at which a final pronounced drop in value occurs indicates the better solution (Petras & Masyn, 2009; Masyn, 2013). Next, the Lo-Mendell Rubin Likelihood Ratio Test (LMR-LRT; Lo, Mendell, & Rubin, 2001) was compared across profiles. The LMR-LRT is a significance test that compares a given model to one with one less profile. A significant value indicates that the more complex profile solution fits better and non-significance favours the lower, or simpler profile solution. An alternate and compliment to the LMR-LRT assessed was the Adjusted Vuong-Lo-Mendell Rubin Test (VLMR-LRT; Vuong, 1989; Lo et al., 2001), which is similar in its interpretation to the LMR-LRT. Next, the average latent profile posterior probabilities were examined to assess the probability that cases were consistently placed in each profile, thereby providing an indication of the classification uncertainty for each profile. Values closer to 1.0 suggest better reliability of classification (Muthén & Muthén, 2000). Finally, the entropy coefficient, an index of profile distinctiveness ranging in values from 0 to 1 was examined. Entropy values closer to 1 were indicative of better fitting solutions, with values greater than .8 considered as noteworthy (Ramaswany et al., 1993).

A complication with the iterative nature of mixture models is that a single set of parameter values will not allow us to find the solution with the best possible LL (Geiser, 2013). The consequence may be that the model estimation terminates at *local* maximum, rather than *global* maximum, thereby providing a solution that fits a portion of the data rather than it as a whole (Geiser, 2013; Masyn, 2013). Such local solutions are associated with incorrect fit statistics and thus should be avoided (Geiser, 2013; Uebersax, 2000). A solution to avoid converging at local maximum is to test the model with various different start values of large numbers. In doing so, if the greatest LL value is reproduced in each of these trials, it suggests that the true global maximum is found (Geiser, 2013; Ubersax, 2000). Thus, the current model was tested with three differing random start values exceeding 2000 and the best log likelihood value was replicated. Further, as recommended by Geiser (2013), a sufficient number of initial stage iterations was used (>50). This suggests that the solution presented herein is an accurate reflection of the data as a whole.

As shown in Table 2, the LL, LMR-LRT, VLMR-LRT suggested a marked improvement when moving from three profiles to four. However, the LL and BIC values suggested an improvement when moving from four profiles to five, but the entropy, average posterior probabilities, LMR-LRT and VLMR-LRT did not. Further inspection of the BIC "elbow plot" (Figure 1) suggests that the five-profile solution did not substantially decrease in fit in comparison to the four-profile. The five-profile solution also rendered a fifth cluster of very small proportion (3%). Thus, in line with the LMR-LRT, VLMR-LRT, average posterior probabilities and entropy, the four-profile solution was retained, despite minimal increases in the LL and BIC in the five-profile solution. This decision also follows Masyn's (2013) recommendation that the more parsimonious solution should be chosen.

In the retained solution, cases were classified into one large and three smaller profiles. Table 3 shows the mean levels of the risk variables in the four profiles and Figure 2 provides a visual demonstration of the profile compositions. Profile 1 comprised the majority (76%) of the sample (n = 703) and will be referred to as the *Low Risk* profile. As hypothesized, it consisted of individuals with the highest mean values of perceived social support and optimism, and the lowest mean values of current financial strain, recent negative life events, neuroticism and negative cognitive style. It also had high levels of childhood subjective SES and low levels of childhood verbal abuse in comparison to the other profiles.

Profile 2 (4% of the sample, *n* = 33) will be referred to as the *Low Social Support Risk* profile, because it consisted of individuals with the lowest mean levels of perceived social support, despite favourable (adaptive) levels on other risk factors. While profiles with small proportions (< 5%) of individuals are typically discouraged in mixture modeling (e.g., Masyn, 2013), this profile was retained because it showed a markedly low and distinct level of social support, was consistently the second profile to emerge in all solutions and remained when a dozen random cases were deleted, thus suggesting it represents an accurate subgroup in the sample.

The third profile (11% of the sample, *n* = 94) will be referred to as the *Financial Risk* profile, because it consisted of individuals with low mean levels of childhood subjective SES and high levels of current financial strain.

The fourth and final profile (8% of the sample, *n* = 73) will be referred to as the *Multiple Risk* profile because it consisted of individuals with the highest mean levels of childhood verbal abuse, recent negative life events, neuroticism and negative cognitive style. This profile also had lowest mean levels of optimism and comparatively low levels of childhood subjective SES relative to the other profiles.

As further validation of the distinctions between profiles, a number of analyses were conducted to determine whether demographic variables (e.g., sex, race, year of study, sexual orientation, history of a mental health diagnosis, employment status, living situation, and age) differed as a function of profile membership. Posterior probabilities were retained and compared across these demographics in SPSS 20.0. Table 4 demonstrates the demographic makeups of the profiles[2].

Chi-square analyses were conducted to examine categorical demographic differences in profile membership. In regard to sex, the profiles did not differ

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[2] Demographic makeup was assessed in SPSS rather than the pseudoclass draws approach in Mplus because some demographic variables were dichotomous and/or nominal. Using the pseudoclass draws approach would render a "mean" on the demographic variables (e.g., one could have a sex of .7), which would not give a clear indication of the makeup of the profile. Thus, the comparisons across demographics may involve some uncertainty in profile membership but give an overall glimpse into the demographic makeup of the profiles.

significantly on their sex makeup, $\chi^2(3) = 9.38$, $p = .15$. The *Low Social Support Risk* profile was 90% female ($n = 30$), while the *Financial Risk* profile was 74% female ($n = 70$), the *Low Risk* profile was 82% female ($n = 577$) and the *Multiple Risk* profile was 89% female ($n = 65$).

The profiles did not significantly differ on their racial makeup either, $\chi^2(9) = 12.74$, $p = .17$. In the *Low Social Support Risk* profile, 69% of participants identified as white ($n = 23$), 15% black ($n = 5$), 3% Asian ($n = 1$) and 12% another racial group ($n = 4$). In the *Financial Risk* profile, 73% of participants identified as white ($n = 69$), 8% black ($n = 8$), 12% Asian ($n = 12$) and 5% another racial group ($n = 5$). In the *Low Risk* profile, 74% of participants identified as white (n = 525), 4% black (n = 35), 12% Asian ($n = 91$), and 7% another racial group (n = 52). In the *Multiple Risk* profile, 75% of the participants identified as white ($n = 55$), 2% black ($n = 2$), 10% Asian ($n = 8$) and 10% another racial group ($n = 8$).

The profiles did not significantly differ on their year of study makeup, $\chi^2(18) = 18.13$, p = .44, with all profiles having an equal distribution of participants in their first, second and third year of university, and less in their fourth and fifth years. Further, the profiles did not significantly differ on their employment status at the time of data collection, $\chi^2(12) = 6.46$, $p = .891$, with the majority of individuals across the profiles being employed part-time.

The profiles did significantly differ on three demographic variables: sexual orientation, history of having had a mental health diagnosis, and living situation. With regards to sexual orientation makeup, $\chi^2(12) = 68.23$, $p < .001$, individuals in the *Multiple Risk* profile had a significantly higher percentage (31%) of participants identifying as homosexual (gay or lesbian), bisexual or pansexual in their sexual orientations, as opposed to those in the *Low Risk* (7%), *Low Social Support Risk* (9%) and *Financial Risk* (12%) profiles. For history of having ever received a mental health diagnosis, $\chi^2(3) = 46.379$, $p < .001$, individuals in the *Multiple Risk* profile had a significantly higher percentage (50%) of participants having had a mental health diagnosis in the past, as opposed to those in the *Low Risk* (25%), *Low Social Support Risk* (33%) and *Financial Risk* (26%) profiles. Regarding living situation, $\chi^2(6) = 21.82$, $p < .001$, the *Low Risk* and *Low Social Support Risk* profiles had a significantly higher percentage (72% in both groups) of individuals living with their parents or guardians as opposed to not, in comparison to those in the *Financial Risk* (57%) and *Multiple Risk* (50%) profiles.

The pseudo-class draw technique was implemented to perform Wald tests of mean differences on age across the four latent profiles (for more details see Muthén & Aparouhov, 2007). Wald chi square analyses revealed that the risk did not significantly differ in their average ages, $\chi^2(3)= 5.80$, $p = .12$, with the average age across the profiles being approximately 21 years.

Differences in Outcome Variables as a Function of Profile Membership

The pseudo-class draw technique was implemented to perform Wald tests of mean differences on distal outcomes across the latent profiles in Mplus. Table 5 displays the means for outcome variables across profiles. Wald chi square analyses revealed that the risk profiles significantly differed in their levels of depressive symptoms, $\chi^2(3)= 43.64$, $p < .001$. Specifically, the *Multiple Risk* profile ($M = 1.14$, $SE = .07$) displayed significantly higher levels of depressive symptoms relative to the *Low Social Support Risk* ($M = .75$, $SE = .08$) and *Low Risk* ($M = .73$, $SE = .02$) profiles. Similarly, the *Financial Risk* profile ($M = 1.02$, $SE = .06$) displayed significantly higher levels of depressive symptoms in comparison to the *Low Social Support Risk* and *Low Risk* profiles.

The profiles also differed significantly on the outcome of anxiety, $\chi^2(3)= 43.64$, $p < .001$. The *Multiple Risk* profile ($M = 1.48$, $SE = .07$) had significantly higher levels of anxiety relative to the *Financial Risk* ($M = 1.28$, $SE = .06$), *Low Social Support Risk* ($M = 1.18$, $SE = .10$) and *Low Risk* ($M = 1.06$, $SE = .02$) profiles. Further, the *Financial Risk* profile showed higher levels of anxiety relative to the *Low Risk* profile.

The differential risk patterned profiles were also significantly associated with different scores in self-esteem, $\chi^2(3)= 27.79$, p < .001. The *Low Risk* profile ($M = 2.04$, $SE = .02$) displayed higher levels of self-esteem in comparison to the *Financial Risk* ($M = 1.82$, $SE = .05$) and *Multiple Risk* profiles ($M = 1.76$, $SE = .06$). The *Low Social Support Risk* profile ($M = 2.03$, $SE = .08$) also displayed significantly higher levels of self-esteem in comparison to the *Multiple Risk* profile.

The profiles differed significantly in their levels of life satisfaction, $\chi^2(3)= 32.51$, $p < .001$. Similar to patterns in self-esteem, individuals within the *Low Risk* profile ($M =$

4.63, *SE* = .05) were more satisfied with life in comparison to those in the *Multiple Risk* (*M* = 4.01, *SE* = .01) and *Financial Risk* (*M* = 4.02, *SE* = .01) profiles. Likewise, individuals within the *Low Social Support Risk* profile (*M* = 5.05, *SE* = .02) were also more satisfied with their lives relative to those within the *Multiple Risk* and *Financial Risk* profiles.

In terms of positive affect, the different risk patterned profiles were not significantly associated with different scores, $\chi^2(3)= 6.97$, $p = .07$. However, the different risk profiles did significantly differ in their levels of negative affect, $\chi^2(3)= 24.52$, $p < .001$. Specifically, those within the *Low Risk* profile (*M* = 2.14, *SE* = .02) had significantly lower levels of negative affect relative to the *Low Social Support Risk* (*M* = 2.39, *SE* = .10), *Financial Risk* (*M* = 2.34, *SE* = .08), and *Multiple Risk* profiles (*M* = 2.51, *SE* = .10).

In terms of subjective academic outcomes, both academic performance (grades) and academic stress were evaluated. The differential risk patterns did not significantly differ on their self-reported academic performance, $\chi^2(3)= 4.04$, $p = .22$. Specifically, the grades within each profile averaged within the B range. The risk profiles did however significantly differ in their levels of subjective academic stress, $\chi^2(3)= 9.18$, $p = .02$. Specifically, those within the *Low Risk* profile (*M* = 1.64, *SE* = .03) reported significantly lower levels of subjective academic stress relative to the *Low Social Support Risk* (*M* = 1.85, *SE* = .10), *Financial Risk* (*M* = 1.85, *SE* = .09) and *Multiple Risk* (*M* = 1.88, *SE* = .12) profiles.

Risk for and Resilience to Depression within the Risk Profiles

Given high rates of depression and depressive symptoms in emerging adults (Blanco et al., 2008; Ibrahim et al., 2013), a follow up analysis was conducted to examine the proportion of markedly depressed students within in each profile. The total score cut off of 16 was used with the CESD to identify those who are at risk for clinical depression (Lewisohn, Seeley, Roberts, & Allen, 1997). Posterior probabilities were retained in SPSS 20.0 and individuals with complete data on the CESD were compared within their most probable profile. Percentages of individuals within each profile with depressive symptoms scores above the cut off were as follows: 39% within the *Low Risk* profile, 41% within the *Low Social Support Risk* profile, 64% within the *Financial Risk* profile, and 63% within the *Multiple Risk* profile. These results suggest that just over a third of individuals within the *Multiple Risk* and *Financial Risk* profiles are resilient to clinical depression, and in turn, a good proportion of those within the *Low Risk* and *Low Social Support Risk* profiles are in danger for developing clinical depression, despite their minimal risk experiences.

Discussion

The present study used a person-centered approach to identify distinct risk profiles among a sample of emerging adults based on a combination of childhood, current contextual and dispositional risk factors, and examined whether these profiles of risk were differentially associated with participants' mental health and academic wellbeing. In line with our hypotheses, person-centered analyses revealed heterogeneity in emerging adults' risk factor experiences. In particular, four risk profiles were identified: a *Low Risk* profile, a *Low Social Support Risk* profile, a *Financial Risk* profile, and a *Multiple Risk* profile. The majority of the sample (76%) made up the *Low Risk* profile, with emerging adults in this subgroup having low to minimal risk factor experiences. A small proportion of the sample (4%) made up the L*ow Social Support Risk* profile, which was characterized with low levels of all risk factors, except social support which was markedly low. The remainder of the sample fell into two risk-prone profiles: the *Financial Risk* (11%) profile, comprised of individuals with low childhood SES and current financial distress, and the *Multiple Risk* (8%) profile, comprised of individuals with multiple maladaptive risk factors. These results suggest that the majority of emerging adults during this period have few risk experiences, but that close to one quarter appear to be vulnerable to poor wellbeing and mental health problems. The presence of these groups underscores the importance of understanding individual differences in emerging adulthood.

Relations between Profile Membership and Mental Health Outcomes

The meaningfulness of the different risk profiles was supported by the differential associations with various measures of mental health and academic wellbeing. With regards to mental health, individuals within the *Low Risk* group were consistently the best off in terms of mental health indicators, including depressive symptoms, anxiety, and negative affect, and comparatively higher levels of positive mental health, such as self-esteem, and life satisfaction. These results accord with our hypothesis that a low risk profile would emerge and support a cumulative risk perspective, which suggests that the absence of risk factors construes an absence of mental health problems (Burchinal et al., 2000). However, emerging adults within the *Low Social Support Risk* group reported levels of depressive symptoms, anxiety, self-esteem, life satisfaction, and positive affect similar to those in the *Low Risk* profile. This suggests that despite markedly low levels of perceived social support, these individuals displayed relatively adaptive wellbeing. This is contradictory to literature that suggests that low social support is detrimental for wellbeing in EA (e.g., Murphy et al., 2010), and instead suggests that low social support may not threaten wellbeing if it acts in isolation from other risk factors. This finding follows the *stress buffering hypothesis*, which states that social support is psychologically protective in its capacity to mitigate stress during stressful situations (Cohen & McKay, 1984; Ditzen et al., 2008), and that low levels are only detrimental if they occur in conjunction with other stressors.[3] For example, social support as a protective asset rather than a risk factor for wellbeing in EA has been demonstrated in several studies on peer support in children (e.g., Adams, Santo, & Bukowski, 2011; Brendgen et al., 2013; Bukowski, Laursen, & Hoza, 2010).

Our finding that the majority of the sample fell within the *Low Risk* and *Low Social Support Risk* profiles and displayed adaptive mental health is consistent with previous research showing that for most, EA is a positive life period (Arnett, 2007; Galambos et al., 2006; Schulenberg & Zarrett, 2006). However, person-centered analyses revealed two distinct profiles at risk for mental health difficulties, the *Multiple Risk* and *Financial Risk* profiles. Consistent with our hypothesis and theories of cumulative risk, individuals with multiple risks fared the worst with regards to depressive symptoms, anxiety, self-esteem, life satisfaction, and negative affect. Yet, for individuals within the *Financial Risk* profile, depressive symptoms, negative affect, self-esteem and life satisfaction were comparably low. This finding highlights a pattern that might have been overlooked by the use of cumulative risk indices, in that having multiple risks and

[3] To test the protective effect of perceived social support in our sample, we ran a series of interactions with social support moderating the relations between several risk factors and wellbeing outcomes. Social support was indeed protective in many cases, suggesting a stress buffering mechanism in our sample.

financial risks may be equally detrimental to emerging adults' mental health. While it cannot be determined for certain, this may also suggest that it is the financial risks that are most predictive of poor mental health in emerging adults, as individuals within the *Multiple Risk* profile also demonstrated lower rates of childhood SES and elevated rates of current financial strain. This is line with previous studies showing that low SES is a key burden to university students (Eisenberg et al., 2007). Interestingly, the rates of employment across the risk profiles did not differ, suggesting that the deleterious effects of low SES hold irrespective of being employed and presumably having some income. However, individuals within the *Financial Risk* and *Multiple Risk* profiles were less likely to still be living with their parents, suggesting that the effects of low SES may be more burdensome for students who are living outside the family home, who presumably have added expenses.

An exception in the pattern of differences among the risk profiles on the mental health indicators was the lack of difference in positive affect. This suggests that the majority of emerging adults are able to experience pleasurable engagement with the environment and positive emotions such as joy, interest, and alertness, irrespective of their risk factor experiences. This holds for individuals within the *Multiple Risk* and *Financial Risk* profiles whom also displayed elevated levels of negative mental health outcomes. Thus, experiencing symptoms of psychopathology does not negate the presence of positive wellbeing in EA, and this underscores the importance of considering both positive and negative outcomes to understand what constitutes adaptive development in EA, beyond just deficits (Keyes, 2007; O'Connor et al., 2012).

While the risk profiles differed with regards to various mental health outcomes, some interesting nuances appeared *within* profiles when mental health diagnosis history and depressive symptom cutoffs were examined. For example, despite low levels of risk, a substantial amount of individuals within the *Low Risk* profile displayed a history of having had a mental health diagnosis (39%) and clinically significant levels of depressive symptoms (25%). This suggests that despite a probability of low risk experiences, many of these individuals are still vulnerable to mental health difficulties and depression. Further, substantial proportions of individuals within the *Multiple Risk* profile lacked a history of a mental health diagnosis (50%), and had depressive symptoms *below* the clinically significant levels (37% below), suggesting resilience despite multiple risk experiences. Clearly, the absence of risk does not guarantee the presence of psychopathology, or vice versa (Cicchetti & Rogosch, 2006; Keyes, 2007).

Relations between Profile Membership and Academic Outcomes

The risk profiles also showed meaning in their relation to subjective academic performance and academic stress. Interestingly, the profiles did not differ across their self-reported academic performance, with all profiles reporting a mean grade within the B range. This suggests that those with risk experiences may be resilient to potentially negative effects on their grades. However, the three risk-prone profiles differed from the *Low Risk* profile in their heightened levels of perceived academic stress. Clearly, despite performing at an adequate level academically, academic demands for a large proportion of students are very stressful. This finding corroborates previous studies showing that many students are overwhelmed by their workloads (American College Health Association, 2015), and is indicative of a need for stress-management programs in order to make university a more manageable experience for risk-prone students.

Limitations and Future Directions

Although this study advances our understanding of how multiple risk factors interact to impact EA wellbeing, it is not without limitations. First, this sample was exploratory as it sought to identify latent profiles within our sample without any specific a priori profile hypotheses. When studies are exploratory, their findings might be dependent on specific sample characteristics. For example, our finding of a small profile (4%) characterized by low social support may be sample-specific. Furthermore, the majority of respondents in this study were female. Thus, replication of these results in other samples is important.

This study was also limited by its cross-sectional nature. This is problematic for the constructs that were measured retrospectively, as retrospective reports, especially those that are negative, may reflect memory or reporting biases (Lalande & Bonanno, 2011). Further, we were unable to show the degree to which profile measurement and membership were stable over time. While some constructs measured were fixed (e.g., childhood abuse), some may vary with time (e.g., current financial strain), limiting the reliability of the classes found here. Thus, longitudinal research is needed to know how class membership may change over time (e.g., latent transition analysis). Likewise, our cross-sectional results do not establish whether different profiles of risk result in different mental health outcomes or if the mental health outcomes impact the experience of risk. For example, more depressed students could be more tired and less likely to work, thereby resulting in financial strain. Future work using prospective longitudinal designs could inform this causal distinction.

An enduring area for future discussion and research would be to examine the theoretical or empirical explanations for the observed relations between risk profiles and wellbeing outcomes. For example, this would be particularly interesting in the instances of resilience described herein, such as academic success despite risk experiences. It is possible that the stress experienced from risk factors motivates drive, grit or challenge to achieve good grades, demonstrating a *steeling effect* (Rutter, 2012). In contrast, perhaps the deleterious outcomes associated with the *Multiple Risk* profile reflect a *sensitization effect*, whereby the effects of previous risks are compounded by further risks (Hammen, Henry, & Daley, 2000; Rutter, 2012). Similarly, explanations for the clinically elevated levels of depression within the low risk profiles are warranted. Investigating other characteristics of individuals and contexts that confer risk and resilience would contribute to our greater understanding of risk in relation to wellbeing in EA. This is especially important because despite average gains in wellbeing, EA is a peak period of risk for mental health problems like depression (Kessler et al., 2005; Rohde et al., 2013).

Finally, all study data were limited to self-report, which is dependent on reporter awareness, accuracy, and willingness to report. Future studies would benefit from mixed-methods and multi-informant data to acquire a full picture of risk and wellbeing in EA.

Implications for Research and Practice

Understanding patterns of risk can inform prevention and intervention programs for university students who may be vulnerable to mental health and academic problems. The specific statistical technique used herein, the identification of latent profiles, is particularly useful for identifying persons who might benefit from different types or dosages of treatment (Collins, Murphy, & Bierman, 2004). The finding that the *Multiple Risk* profile fared the least well regarding mental health suggests a cumulative risk function, where targets for intervention could be widespread, across the life course and current context. Yet, given that the *Financial Risk* profile was comparable to the *Multiple Risk* profile in many instances, and that the *Multiple Risk* profile also suffered from financial difficulties, an efficient target for intervention may include targeting students' finances. Specifically, efforts to provide financial support through grants, lowered tuition and living costs for university-enrolled emerging adults may be paramount in improving mental health in this population. Such interventions would also be especially vital given the increasing number of students reporting university debt (Allen, Shelley, & Butlin, 2003).

The finding that many university students in our sample suffered from elevated rates of perceived academic stress suggests that intervention efforts would be well-utilized in helping students cope with these demands. Some studies have also shown that students' perceptions of their work demands contribute to their mental health (Ang & Huan, 2006; Maroco & Campos, 2012), making it a far-reaching target for intervention. Specifically, university run stress-management programs show promise in some student samples (e.g., Redwood & Pollak, 2006). Similarly, given the elevated rates of mental health across all of risk profiles, services that target students' mental health and coping with life events is warranted. Such interventions would be especially beneficial if implemented with some form out-reach, given that despite high rates of psychiatric disorders, few college students actually seek out treatment (Blanco et al., 2008; Eisenberg et al., 2007).

Conclusion

It is clear that the transitory nature of emerging adulthood poses both threats and opportunities to wellbeing. As an attempt to better understand diversity in wellbeing during this life period, this study applied a person-centered approach to examine how various risk factors relate to mental health and academic wellbeing in a large sample of university enrolled emerging adults. Consistent with the heterogeneity of emerging adulthood, the person-centered methodology revealed a number of underlying subgroups with different experiences of risk, which were differentiated by various mental health and wellbeing outcomes. The results suggest the importance of distinct targeted intervention strategies, as varied types of emerging adults were vulnerable to compromised mental health and academic stress.

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Table 1

Means, Standard Deviations and Correlations between all Study Variables

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.
1. Childhood subjective SES	-															
2.Childhood verbal abuse	-.18**	-														
3. Financial strain	-.23**	.20**	-													
4. Negative life events	-.12**	.31**	.40**	-												
5. Social support	.08*	-.16**	-.12**	-.13**	-											
6. Neuroticism	-.07*	.17**	.14**	.23**	-.17**	-										
7. Optimism	.14**	-.17**	-.13**	.13**	.22**	-.45**	-									
8. Cognitive style	-.09*	.16	.11**	.22**	-.16**	.44**	-.51**	-								
9. Depressive symptoms	-.18**	.29**	.25**	.26**	-.31**	.54**	-.52**	.43**	-							
10. Anxiety	-.08*	.18**	.18**	.27**	-.21**	.60**	-.43**	.40**	.58**	-						
11. Life satisfaction	.27**	-.22**	-.21**	-.17**	.28**	-.35**	.52**	-.30**	-.54**	-.33**	-					
12. Self-esteem	.18**	-.23**	-.18**	-.18**	.30**	-.47**	.64**	-.54**	-.63**	-.45**	.59**	-				
13. Positive affect	.16**	-.03	-.07*	-.05	.19**	-.27**	.45**	-.35**	-.45**	-.22**	.45**	.45**	-			
14. Negative affect	-.05	.20**	.14**	.19**	-.21**	.49**	-.34**	.30**	.68**	.59**	-.30**	-.40**	-.13**	-		
15. Academic performance	.05	-.02	-.09**	-.02	.14**	-.01	.15**	-.02	-.14**	-.04	.14**	.15**	.09**	-.08**	-	
16. Academic stress	-.14**	.12**	.12**	.15**	-.19**	.31**	-.47**	.34**	.51**	.39**	-.40**	-.52**	-.39**	.39**	-.36**	-
M	7.93	1.20	.41	.88	5.52	2.88	2.39	3.00	.80	1.13	4.52	1.98	3.07	1.29	6.34	1.7
SD	1.74	1.20	.44	1.15	1.31	.76	.79	.62	.52	.56	1.34	.52	.79	.71	1.27	.75

$^{**}p < .001$ $^{*}p < .05$

Table 2

Fit Statistics for Full-Sample LPA Models with 1-5 Profiles

No. of Profiles	LL	BIC	LMR-LRT	VLMR-LRT	AvePP	Entropy
1	1.12	17370.95	-	-	**1.0**	-
2	1.05	16068.46	$p < .001$	$p < .001$	**.99**	**.96**
3	1.08	16829.09	$p < .001$	$p < .001$	**.98**	**.94**
4	**1.16**	16669.28	$\boldsymbol{p = .01}$	$\boldsymbol{p = .01}$	**.95**	**.91**
5	**1.17**	**16601.14**	$p = .08$	$p = .08$	.92	.89

Note. LL = scaled loglikelihood (corrected for FIML); BIC = Bayesian Information Criterion; LMR-LRT = Lo-Mendell Rubin Likelihood Ratio Test; VLMR-LRT = Adjusted Vuong-Lo-Mendell Rubin Test; AvePP = Average of the Posterior Probabilities. Bolded values indicative of the better fitting model.

Table 3

Risk Factor Indicator Means for the 4-Profile Model

	Risk Profiles			
Risk Factors	Low Risk (n = 703)	Social Support Risk (n = 33)	Financial Risk (n = 94)	Multiple Risk (n = 73)
Childhood Risks				
Childhood verbal abuse	1.04	.84	1.57	2.06
Childhood subjective SES	8.07	8.18	7.28	7.39
Current Situational Risks				
Financial strain	.23	.29	1.28	.71
Perceived social support	5.80	1.29	5.38	5.23
Recent negative life events	.53	.64	1.33	3.58
Dispositional Risks				
Optimism	2.43	2.57	2.18	2.14
Neuroticism	2.82	2.82	3.03	3.25
Cognitive style	2.95	2.94	3.05	3.35

Table 4

Differences in Demographic Variables as a Function of Profile Membership

	Risk Profiles				
Demographic Variables	Low Risk (n = 703)	Low Social Support Risk (n = 33)	Financial Risk (n = 94)	Multiple Risk (n = 73)	χ^2 value
Sex					9.28^{ns}
Male	18%	10%	26%	11%	
Female	82%	90%	74%	89%	
Race					12.74^{ns}
White	74%	69%	73%	75%	
Black	4%	15%	8%	2%	
Asian	12%	3%	12%	10%	
Another race	7%	12%	5%	10%	
Sexual Orientation					68.23**
Heterosexual	92%	91%	88%	65%	
Gay or Lesbian	4%	6%	6%	11%	
Bisexual	2%	3%	4%	10%	
Pansexual	1%	0%	2%	10%	
History of MH Diagnosis					46.37**
No	75%	67%	74%	50%	
Yes	25%	33%	26%	50%	
Year of Study					18.13^{ns}
1st year	27%	22%	35%	23%	
2nd year	31%	44%	22%	22%	
3rd year	27%	18%	28%	29%	
4th year +	15%	16%	15%	26%	
Employment Status					6.46^{ns}
Not employed	32%	30%	33%	31%	
Part-time	60%	66%	54%	59%	
Full-time	3%	0%	5%	5%	
Seasonal/temporary	5%	3%	8%	5%	
Living Situation					21.82**
With parent(s)/guardian(s)	72%	72%	57%	50%	
Not with parent(s)/guardian(s)	28%	28%	43%	50%	
Age					5.80^{ns}
M	21.08	21.01	21.08	21.70	
SE	.06	.33	.20	.23	

**p <.001

Table 5

Differences in Outcome Variables as a Function of Profile Membership

	Risk Profiles			
Wellbeing Outcomes	Low Risk *M* (*SE*)	Low Social Support Risk *M* (*SE*)	Financial Risk *M* (*SE*)	Multiple Risk *M* (*SE*)
Depressive symptoms	.73 (.02)[b,c]	.75 (.08)[a,d]	1.02 (.06)[c,d]	1.14 (.07)[a,b]
Anxiety	1.06 (.02)[a,d]	1.18 (.10)[b]	1.28 (.06)[c,d]	1.48 (.07)[a,b,c]
Self-esteem	2.04 (.02)[a,b]	2.03 (.08)[c]	1.82 (.05)[a]	1.76 (.06)[b,c]
Life satisfaction	4.63 (.05)[a,b]	5.05 (.02)[c,d]	4.02 (.01)[a,c]	4.01 (.01)[b,d]
Positive affect	3.10 (.03)	3.15 (.14)	2.91 (.09)	2.94 (.10)
Negative affect	2.14 (.02)[a,b,c]	2.39 (.10)[a]	2.34 (.08)[b]	2.51 (.10)[c]
Academic performance	6.39 (.05)	6.09 (.23)	6.10 (.13)	6.30 (.15)
Academic stress	1.64 (.03)[a,b,c]	1.85 (.10)[a]	1.85 (.09)[b]	1.88 (.12)[c]

Note. Means with matching letters are significantly different from one another based on Wald chi-square tests.

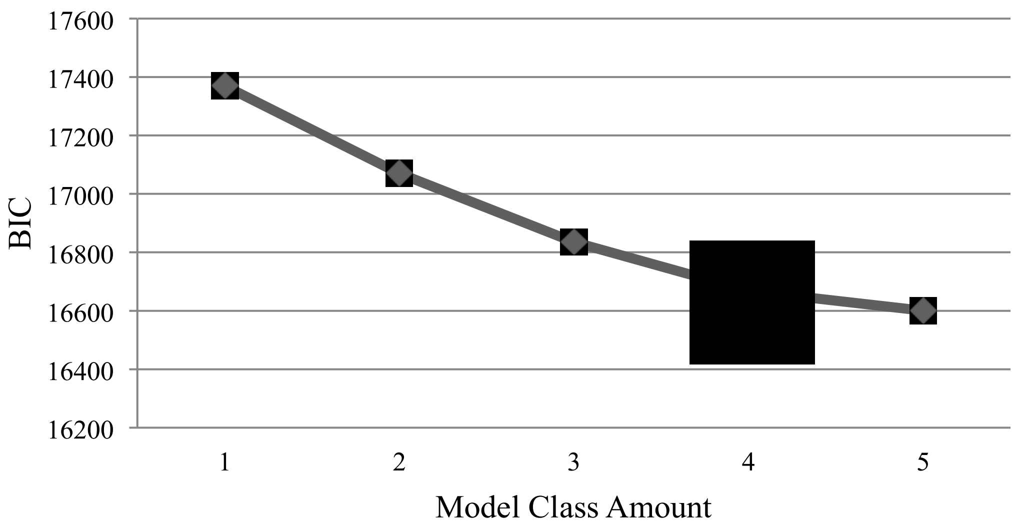

Figure 1. “Elbow plot” of Bayesian Information Criterion (BIC) values across 1-5 profile models.

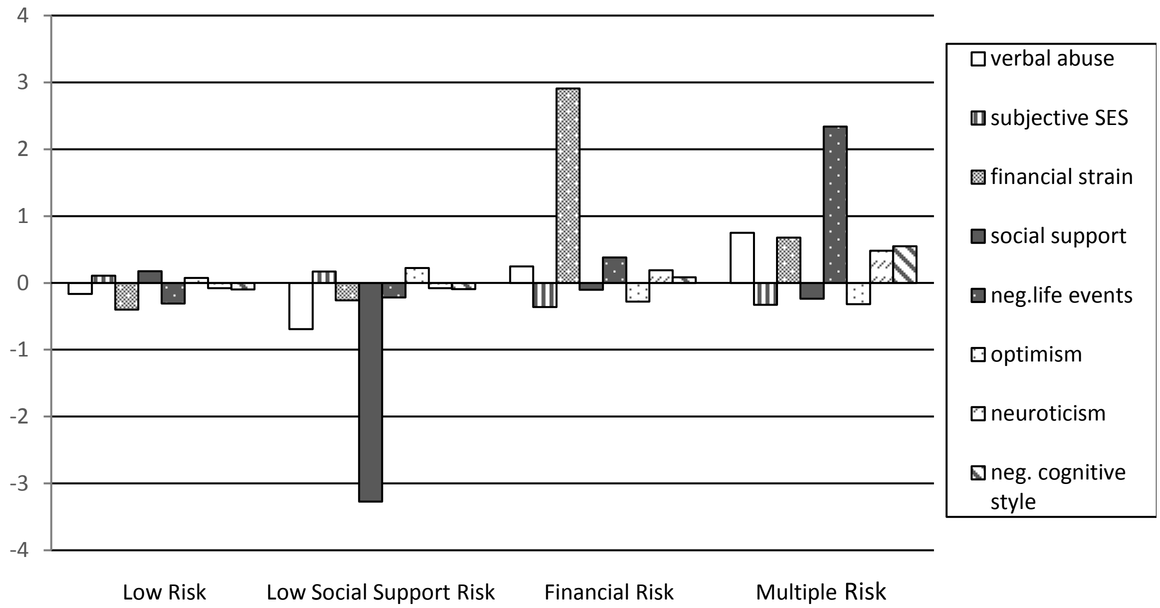

Figure 2. Characteristics of the latent profiles on the predictor risk variables. The results were standardized for ease of interpretation.

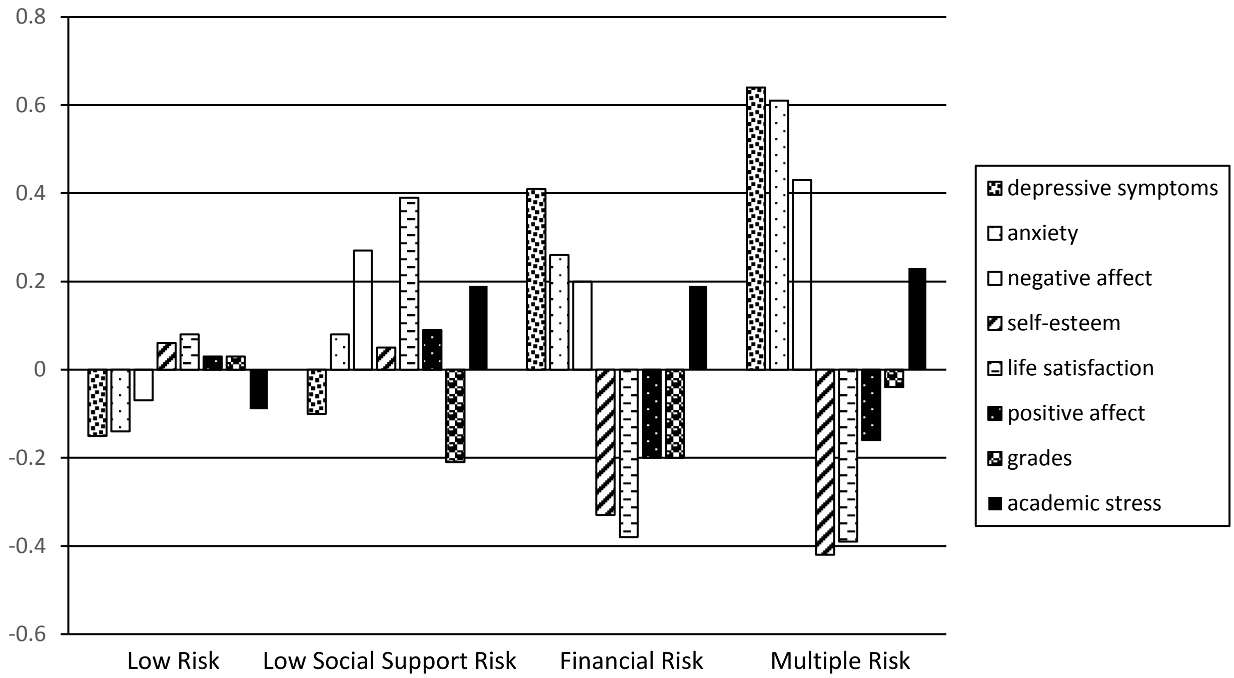

Figure 3. Characteristics of the latent profiles on the outcome variables. The results were standardized for ease of interpretation.