



# Trajectories of Affective Balance 1 Year After Traumatic Injury: Associations with Resilience, Social Support, and Mild Traumatic Brain Injury

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## Abstract

We examined trajectories of affective balance (AB) among 488 individuals admitted to a metropolitan Level 1 trauma center for serious physical injury. AB was measured prior to hospital discharge, and at three, six, and 12 months post-discharge. Multilevel modeling (MLM) was used to investigate whether initial demographic variables, injury severity, the occurrence of a mild traumatic brain injury (TBI), self-reported resilience and social support predicted AB trajectories. Participants' change in resilience and social support over the 12-month period were also tested as predictors. The results revealed a large amount of between-individual variation in the first year post-injury. Initial resilience, resilience change, initial social support, and social support change predicted AB 1 year later. Changes in resilience and social support predicted the linear growth in AB over time. Demographic and injury-related variables did not significantly predict AB, nor did the diagnosis of a mild TBI. Participants' self-perceived resilience and social support scores changed substantially, for better or worse, over the 12-month period. AB was strongly associated with these changes, even when controlling for initial resilience and social support: Increases in either resilience or social support were significantly associated with increases in AB over time. The final model accounted for 33.2% of the between-individual variance in final scores and 46.9% of the variance in linear growth. These results provide additional evidence of the beneficial effects of existing levels of resilience and social support following traumatic injury, and these characteristics are better predictors of AB than injury severity, basic demographic data, and the presence of a mild head injury. Furthermore, changes that may occur in social support and self-perceived resilience are associated with significant changes in AB, and these factors should be considered in post-discharge plans to facilitate subsequent adjustment.

**Keywords** Affective balance · Well-being · Traumatic injury · Mild traumatic brain injury · Resilience · Social support · Multilevel modeling

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## 1 Introduction

Each year approximately 3 million Americans are hospitalized after sustaining a traumatic physical injury (Centers for Disease Control [CDC] 2013). As medical advances have improved survival rates and medical outcomes for individuals who sustain a traumatic injury, focus has shifted to understanding, predicting, and promoting psychological and social well-being after the injury. Traumatic injury has been linked to psychological distress and poorer mental health functioning (Bryant et al. 2010; Wiseman et al. 2012). Diminished mental health functioning, in turn, negatively impacts individuals' physical health, daily activities, coping skills, and ability to function in work and other roles (Halcomb et al. 2005; Zatzick et al. 2008).

In contrast, subjective well-being (SWB) as conceptualized by Diener (1984) is strongly associated with improved health and longevity, better ability to cope with stressors, healthier social behaviors, and overall, greater productivity and engagement with life (Diener 2012; Fredrickson 2013; Lyubomirsky et al. 2005). Emotional well-being (EWB) comprises two of the three components of SWB—the relative presence of positive affect and negative affect—and represents a person's "hedonic" balance of pleasant and unpleasant emotions over time (Diener 1984; Lucas et al. 1996). Information about EWB depends on a meaningful appreciation and measurement of the balance between ongoing positive and negative affective experiences that are critical to quality of life (National Research Council 2013). Policymakers, in particular, are interested in affective balance (AB) because it can potentially provide information about the relative degree of suffering and contentment essential to quality of life that may be addressed in programs to reduce the former, and facilitate the latter (National Research Council 2013).

Unfortunately, the majority of relevant studies of individuals who incur traumatic injuries focus primarily on life satisfaction, and AB is largely ignored. Studies that do examine affect as the outcome variable of interest focus almost invariably on affective distress reactions or mood disorders. Consequently, much is known about life satisfaction and negative affective reactions following traumatic injury, but there is a dearth of information concerning AB after traumatic injury.

Furthermore, it is unclear to what extent AB is affected following traumatic injury. In some studies AB appears susceptible to short-term changes following major life events, while other work suggests that it is too closely related to stable personality traits to yield large, lasting fluctuations (Diener et al. 2006; Luhmann et al. 2012). Hedonic adaptation models (Frederick and Loewenstein 1999) propose that the emotional impact of even traumatic life events diminishes over time, so people inevitably adapt back to their pre-trauma levels of AB. Yet longitudinal studies that track SWB levels as people "adapt" to their injuries over time have yielded inconsistent results. Studies that examine individual trajectories over time, rather than relying solely on average scores, provide considerable insight into these inconsistent results by revealing significant individual variation in SWB trajectories following traumatic injury (Hernandez et al. 2014; van Leeuwen et al. 2012).

Evidence suggests that psychological factors may have considerably more influence on AB following traumatic injury than demographic and injury-specific variables. For example, gender, race/ethnicity, and injury-specific variables (e.g., degree of paralysis, completeness of lesion) account for less than one percent to approximately 12% of the variance in trajectories of life satisfaction following moderate and severe traumatic brain injury (TBI; Williamson et al. 2016) and spinal cord injury (SCI; Pretz et al. 2016). In contrast, studies that include characteristics such as family satisfaction, social support, and

self-efficacy account for 31% (Hernandez et al. 2014) to 66% (van Leeuwen et al. 2012) of the explained variance in life satisfaction trajectories post-injury.

This pattern does not rule out the possible deleterious effects that may be associated with certain injuries. Traumatic brain injuries are among the more frequent conditions treated in trauma centers (accounting for 2.2 million emergency department visits in the United States; CDC 2010), and TBIs are often associated with significant psychological problems (Bryant et al. 2015) and lower life satisfaction (Braden et al. 2012) in the initial year following trauma care. These problems can also develop into chronic conditions that necessitate ongoing medical and psychological services (Zgaljardic et al. 2015). Our current understanding of these issues is based on studies of individuals with moderate to severe TBI. Studies of AB among persons who incur mild TBI (mTBI) are few, although preliminary work finds that individuals with mild to moderate TBI report significantly lower happiness than individuals with traumatically acquired spinal cord injuries and others with severe fractures 1 year post-injury (McCord et al. 2016).

Social support and resilience represent two psychological factors with particularly strong associations with AB. Positive emotions usually accompany close relationships, and happy individuals are more likely to engage in and cultivate successful social interactions, and report satisfying friendships and support (Armenta et al. 2015). Self-reported resilience is also positively associated with positive emotions, and this may be one of the primary mechanisms through which it facilitates optimal adjustment following traumatic disability (Dunn et al. 2017; Walsh et al. 2016). However, the degree to which self-reported resilience would predict AB over the course of a year is somewhat uncertain: Although self-reported resilience is significantly associated with indicators of psychological adjustment after 12 months among individuals with physical disabilities, it may account for small percentages of variance in these outcomes (e.g., one and two percent; Silverman et al. 2015).

We conducted the present study to test the degree to which social support, resilience, injury severity, and mTBI would predict AB in the first year following treatment at a Level 1 trauma center in a metropolitan area. We hypothesized higher levels of social support and self-perceived resilience would predict higher levels of AB. We also hypothesized that more severe injuries and the presence of mTBI would predict lower levels of AB. We used multilevel modeling (MLM) techniques to model participants' individual trajectories over time using unique characteristics (i.e., resilience, social support) as predictors, while simultaneously controlling for demographic and injury-related variables that are typically deemed clinically important, including the occurrence of a mild TBI. Our models were also construed to be sensitive to possible changes over time in resilience and social support, and to examine the impact of these changes on AB trajectories.

## 2 Method

### 2.1 Participants

Participants were part of a larger project conducted by researchers at the Baylor University Medical Center (BUMC) Trauma Division. This project was designed to measure health-related quality of life outcomes among patients during a 1-year period following their discharge from the Baylor Scott & White Trauma Center in Dallas, Texas. Patients were eligible for inclusion if they were age 18 or older and admitted to the

Trauma Service with an admission of at least 24 h. Patients were excluded if they were unable to understand spoken English or Spanish, or if they had a TBI and/or any pre-morbid cognitive deficits (i.e. dementia) severe enough to impair their ability to provide informed consent. The original study was approved by and conducted under the auspices of the institutional review boards at Texas A&M University and BUMC.

Once medically stable, qualifying individuals were informed about the study and invited to participate. After providing informed consent, participants were formally entered into the study. Participants completed initial questionnaires prior to being medically discharged (i.e., at Time1). Trained interviewers then followed up with participants by phone to administer subsequent measures at 3 months post-discharge (Time2), 6 months post-discharge (Time3), and 12 months post-discharge (Time4). The three- and six-month follow-ups were conducted within a 4-week window around each participant's target date, while the 12-month follow-up was conducted within a 4-month window. Unless a participant declined to continue participation, researcher investigators continued to attempt to contact participants at each follow-up.

Of the 505 qualifying participants who consented, 488 had data for at least one time point and were subsequently included in the study. Participants ranged in age from 18 to 92, with a mean age of 44.41 ( $SD = 16.92$ ). There were 314 men (64%) and 174 (36%) women in the sample. Most of these participants identified as Caucasian/White (67.4%;  $n = 329$ ), followed by African American/Black (24.4%;  $n = 119$ ), Multiracial (3.9%;  $n = 19$ ), American Indian or Alaskan Native (1.8%;  $n = 9$ ), Asian (.6%;  $n = 3$ ), and Native Hawaiian or Pacific Islander (.4%;  $n = 2$ ). About one-fifth of the sample identified as Hispanic (18.6%;  $n = 91$ ). Most participants were never married (37.5%;  $n = 183$ ); others were either married (33.2%;  $n = 162$ ), divorced (19.1%;  $n = 93$ ), widowed (6.6%;  $n = 32$ ), or separated (2.5%;  $n = 12$ ). More participants were employed (57.0%;  $n = 278$ ) than unemployed (43.0%;  $n = 210$ ).

## 2.2 Measures

### 2.2.1 Resilience

Resilience was measured with the Connor-Davidson Resilience Scale 10 (CD-RISC 10; Campbell-Sills and Stein 2007), a self-report questionnaire derived from the original 25-item CD-RISC (Connor and Davidson 2003). The CD-RISC 10 is strongly correlated with the original 25-item CD-RISC ( $r = .92$ ; Campbell-Sills and Stein 2007), and it has demonstrated a unidimensional factor structure (Burns and Anstey 2010; Farkas and Orosz 2015) and acceptable internal consistency (.85, Campbell-Sills and Stein 2007; .87, .90; Hartley 2012). The questionnaire consists of 10 Likert-type items ranging from "Not true at all" (0) to "True nearly all the time" (4) that capture four dimensions of resilience: hardiness, social support/purpose, faith, and persistence. The 10-item version has demonstrated considerable construct validity in its associations with an array of self-report resilience and adjustment measures (Campbell-Sills and Stein 2007; Farkas and Orosz 2015). Total CD-RISC scores, ranging from 0 to 40, were used in the current study. Higher scores reflect greater self-reported resilience. Resilience was measured at Time1 (i.e., prior to hospital discharge) and Time4 (i.e., 12 months post-discharge).

## 2.2.2 Social Support

Social support was measured using the Social Provisions Scale (SPS; Cutrona and Russell 1987). The SPS was developed based on Weiss's (1974) model, which conceptualizes relationships with others as providing six different "provisions," or social functions: (1) guidance, (2) reliable alliance, (3) reassurance of worth, (4) opportunity for nurturance, (5) attachment, and (6) social integration. The SPS has demonstrated acceptable internal consistency (.84 to .92) and it correlates appropriately with satisfaction with support ( $r = .35$ ), number of supportive persons ( $r = .40$ ), number of helping behaviors ( $r = .35$ ), and attitudes toward support ( $r = .46$ ; Cutrona and Russell 1987). Test-retest reliability for the total score obtained from a sample of older adults was .55 over a 6-month period (Cutrona et al. 1986). Studies comparing the SPS with other instruments (Cutrona 1984) and interactional behaviors in daily encounters (Cutrona 1986) provide evidence of validity. The instrument contains 24 Likert-type items ranging from "Strongly disagree" (1) to "Strongly agree" (4). Total SPS scores, ranging from 24 to 96, were used in the current study. Higher scores reflect more self-perceived social support. Social support was measured at Time1 and Time4.

## 2.2.3 Resilience Change and Social Support Change

Resilience and social support change scores were computed for participants who had scores on the respective measures at both Time1 and Time4. A simple difference score was calculated as  $D = Y - X$ , where  $X$  is the (CD-RISC 10 or SPS) total score at Time1 and  $Y$  is the (CD-RISC 10 or SPS) total score at Time4.

## 2.2.4 Demographic Variables

Demographic variables included age, gender, racial/ethnic minority status, marital status, employment status, and education. Age was the participant's chronological age at the time of admission. Gender was coded as male/female. Participants who were both Caucasian and non-Hispanic were coded at 0 (non-minority status), while other participants were coded at 1 (minority status). Dichotomous demographic variables also included marital status (1 = married, 0 = any other marital category), employment status (1 = employed, 0 = unemployed), and education (1 = any degree above a high school degree, 0 = high school degree or less).

## 2.2.5 Injury Variables

Injury-related variables were derived from diagnostic information entered into the medical record by the attending trauma surgeon and subsequently recorded by a trauma nurse clinician into the hospital's trauma registry. Ratings of injury severity and occurrence of mild traumatic brain injury (mTBI) at injury were obtained from the registry.

Injury severity was assessed with the Injury Severity Score (ISS; Baker et al. 1974). The ISS provides an overall score of injury severity, can account for multiple injuries on the body, is routinely used in emergency settings, and correlates strongly with mortality and length of hospital stay (Baker et al. 1974; Semmlow and Cone 1976). ISS scores range from 0 to 75, with 75 indicating a fatal injury. Individuals with ISS scores greater than 50 were not included in the study.

Participants were coded as either positive (1) or negative (0) for mTBI based on International Classification of Diseases (ICD) diagnostic codes that were assigned to them during their hospitalization (e.g., ICD-9 codes 850.0, 850.1, 850.11, 850.12). Patients with moderate and severe TBI were excluded from the study. Of the 488 participants, 131 (26.8%) had an mTBI diagnosis.

## 2.2.6 Affective Balance

Affective balance (AB) was measured at all four time points using the Mental Health (MH) subscale of the Veterans RAND 12-Item Health Survey (VR-12). The VR-12 is a widely used and nonproprietary version of the SF-12 health-related quality of life measure developed for and used by the United States Veterans Health Administration (Kazis et al. 2006). Guided by item response theory, the SF-12 was developed as a shorter iteration of the 36-item version that assessed quality of life in eight domains, including mental health (Ware et al. 1996). The items for the SF-12 were identified in regression analyses to account for over 90% of the available variance in the summary scores (Ware et al. 1996). The two items on the MH subscale—“How much of the time during the past 4 weeks have you felt calm and peaceful?” and “How much of the time during the past 4 weeks have you felt downhearted and blue?”—accounted for the majority of variance in the original MH total score on the larger instrument (Ware et al. 1996). The two-item MH subscale significantly correlates in expected directions with a depression screening device ( $-.69$ ), a measure of distress ( $-.75$ ), and self-reported mental health ( $-.45$ ; Fleishman and Zuvekas 2007). Scores on the MH subscale also significantly and predictably differ between individuals with minor medical concerns and those with more severe mental and physical diagnoses (Ware et al. 1996). The combination of items that assess positive and negative affective experiences provides information about both ends of the affective balance spectrum (National Research Council 2013; p. 40), and the 4-week time frame for responses increases the likelihood that a stable pattern of affective experience is assessed.

Responses are Likert-type (1 = All of the time, 6 = None of the time) and coded such that higher scores indicate the respondent “feels peaceful, happy and calm” most of the time (Ware 1993, p. 35). MH scores were normed using 1998 U.S. population data and then transformed into standardized *T*-scores, consistent with SF-12 scoring procedures (Ware et al. 2002). In the present sample, the MH items had alpha internal reliability coefficients of .70 at Time1 ( $n=486$ ), .74 at Time2 ( $n=345$ ), .81 at Time3 ( $n=267$ ), and .80 at Time4 ( $n=244$ ).

## 2.3 Data Analysis

Multilevel modeling (MLM) was used to investigate individual trajectories of AB over time using variables of individual difference (i.e., demographic variables, injury characteristics, resilience, and social support). MLM controls for the inherent correlation of repeated measurements and allows individual growth trajectories to vary based on growth parameters specified by the researcher (Quené and van den Bergh 2004; Raudenbush and Bryk 2002). This approach allows researchers to investigate both the between- and within-individual variation in growth rates (Wallace and Green 2002) and determine if between-individual variation is “systematically related to various contextual factors” (Willett et al. 1998, p. 398). Furthermore, MLM readily accommodates missing data and unequally spaced measurement intervals, and is flexible in regards to specifying the variance–covariance structure

(Hox 2010; Kwok et al. 2008; Quené and van den Bergh 2004). As a result, MLM can provide greater statistical power and more accurate parameter estimation than alternative statistical techniques.

Hierarchical Linear Modeling-7 (HLM-7) was used for model building and evaluation. IBM SPSS Statistics 24 was used to obtain descriptive statistics and graphical information and test for assumption violations. A time variable was created and coded as  $-12$ ,  $-9$ ,  $-6$ , and  $0$  for Time1 to Time4, respectively, so that the intercept represents predicted AB at 12 months post-injury. Three growth patterns were tested: linear, quadratic, and cubic growth. For participants with partially completed measures (1.6%), missing scores were imputed using the mean of completed item scores if at least 70% of the items were answered. Three outliers were identified using standardized score cutoffs of  $-4/+4$  and managed with windsorization. After recording the raw descriptive statistics for all variables, the resilience and social support variables were converted to a 0–100 scale to enhance interpretability. Continuous predictors were centered on their respective grand means.

Model building was approached in a stepwise fashion using data-driven procedures. The best-fitting growth pattern and error covariance structure was selected using  $\chi^2$  likelihood ratio tests. Demographic and injury-related variables were entered into a transitional model as potential predictors of the random intercept and random linear effect of time.  $p$  values were used to identify the non-significant predictors, which were then removed. Next, resilience and social support variables were entered into a second transitional model and also tested as predictors, while controlling for significant demographic and injury-related variables identified in the previous step. Again,  $p$  values were used to remove any non-significant predictors from the model. The Pseudo- $R^2$  statistic proposed by Raudenbush and Bryk (2002) was used to evaluate the predictive ability of the final model. Pseudo- $R^2$  statistics were also calculated for each resilience and social support variable individually in order to determine their unique ability to predict AB. Details regarding the equations used are available upon request.

## 3 Results

### 3.1 Preliminary Analyses

#### 3.1.1 Affective Balance (AB)

Mean AB scores for each measurement occasion are presented in Table 1. The mean AB score across all participants and all measurement occasions was 48.96 ( $SD=12.73$ ). On average, there was a decrease in AB from Time1 to three months post-discharge, followed by small increases from 3 to 6 months and again from 6 to 12 months post-discharge. At Time1, AB was significantly predicted by marital status [ $F(1, 481)=4.95, p=.03$ ] and employment status,  $F(1, 484)=18.68, p<.01$ . Married and employed individuals at admission reported greater AB on average than unmarried and unemployed individuals. At 12 months post-discharge (Time4), AB was significantly predicted by employment status [ $F(1, 242)=4.36, p=.04$ ] and education,  $F(1, 242)=13.35, p<.01$ . Individuals who were employed and had higher levels of education reported greater AB on average 12 months post-discharge than unemployed individuals and individuals with lower educational attainment.

**Table 1** Descriptive statistics for repeated measurement variables

Time	AB				Resilience				Social support			
	Mean	SD	<i>n</i>	% missing	Mean	SD	<i>n</i>	% missing	Mean	SD	<i>n</i>	% missing
T1	51.33	11.30	486	.4	31.96	6.44	469	3.9	79.14	11.06	416	14.8
T2	46.99	13.17	345	29.3								
T3	47.61	13.49	267	45.3								
T4	48.51	13.25	244	50.0	31.28	7.39	239	51.0	76.23	11.16	237	51.4

T1=Prior to hospital discharge, T2=3 months post-discharge, T3=6 months post-discharge, T4=12 months post-discharge

### 3.1.2 Resilience and Social Support

Mean resilience and social support scores for Time1 and Time4 are also displayed in Table 1. At Time1, resilience was significantly predicted by employment status [ $F(1, 467)=16.39, p<.01$ ] and mTBI status,  $F(1, 460)=9.01, p<.01$ . Individuals who were unemployed and/or who had sustained an mTBI reported lower levels of resilience on average than individuals who were employed and/or had no occurrence of mTBI. Also at Time1, social support was significantly predicted by marital status [ $F(1, 413)=10.92, p<.01$ ], employment status [ $F(1, 414)=17.62, p<.01$ ], and education,  $F(1, 414)=7.11, p=.01$ . Being married, being employed, and having more educational attainment was related to greater self-reported social support. At Time4, social support was significantly predicted by employment status [ $F(1, 235)=6.03, p=.02$ ] and education,  $F(1, 235)=25.34, p<.01$ .

For the 233 participants with resilience scores at both Time1 and Time4, the mean percent change was  $-.58\%$  ( $SD=17.60$ ) and the mean absolute percent change was 13.05%. For the 202 participants with social support scores at both Time1 and Time4, the mean percent change was  $-4.81\%$  ( $SD=15.18$ ) and the mean absolute percent change was 11.94%.

### 3.1.3 Missing Data

Of the 488 participants in the study, 109 (22%) had AB scores for only one time point, 93 (19%) had scores for two time points, 97 (20%) had scores for three time points, and 189 (39%) had scores for all four time points. Missing data in the sample increased as time progressed (see Table 1), with panel dropout (attrition) accounting for 78% of the missing data cases. The largest drop in participant response rate occurred between Time1 and Time2. Difficulty contacting trauma patients following discharge is well documented in the literature (Aaland et al. 2012), and it is reported that upwards of 81% of trauma patients have at least one change in cell phone number over the course of 6 months (Kelly et al. 2017), making follow-up phone interviews, based on information given at time of hospitalization, difficult.

HLM has the capacity to make use of all available data, including incomplete cases, by assuming that the data are missing at random (MAR) and using a maximum likelihood (ML) estimation method. When the assumption is that data are MAR, "...the missingness may depend on other variables in the model, and through these be correlated with



the unobserved values” (Hox 2010, p. 106). Attrition analyses were conducted to compare the participants with complete data ( $N=189$ ) against the participants with incomplete data ( $N=299$ ) on demographic and injury-related variables, and on AB scores at each time point (see Table 2).

Whether an individual had complete data was related to age [ $F(1, 486)=29.16, p<.01$ ], gender [ $\chi^2(1, N=488)=5.07, p=.02$ ], marital status [ $\chi^2(1, N=485)=8.27, p<.01$ ], and education,  $\chi^2(1, N=488)=6.21, p=.01$ . Being older, female, married, and having more educational attainment tended to increase, on average, the chance that a participant would have complete data. In addition, there were significant relationships between data missingness and AB scores at Time2 [ $F(1, 343)=7.43, p<.01$ ] and Time3,  $F(1, 265)=8.24, p<.01$ . Participants with complete data tended to have higher AB scores than participants with incomplete data.

The associations between missingness and several other variables in the study indicate that, conditional on those variables, the missing data mechanism was, at minimum, not missing completely at random (MCAR). It is possible that the current data was missing not at random (MNAR). However, there is no formal test to empirically verify MNAR data missingness for the current study. Overall, given the associations between missingness and

**Table 2** Variable statistics for participants with complete versus incomplete data

	Participants with complete data ( $n=189$ )	Participants with incomplete data ( $n=299$ )	$p$ value <sup>a</sup>
Age mean (standard deviation)	49.48 (16.85)	41.21 (16.21)	<.01
Gender			
Female	79 (41.8%)	95 (31.8%)	.02
Male	110 (58.2%)	204 (68.2%)	
Racial/ethnic minority status			
No	106 (56.1%)	141 (47.2%)	.07
Yes	82 (43.4%)	153 (51.2%)	
Marital status			
Other	110 (58.2%)	213 (71.2%)	<.01
Married	77 (40.7%)	85 (28.4%)	
Employment status			
Unemployed	84 (44.4%)	126 (42.1%)	.62
Employed	105 (55.6%)	173 (57.9%)	
Education			
High school degree or less	94 (49.7)	183 (61.2%)	.01
Any advanced degree	95 (50.3%)	116 (38.8%)	
mTBI status			
No	136 (72.0%)	214 (71.6%)	.89
Yes	50 (26.5%)	81 (27.1%)	
ISS mean (standard deviation)	12.01 (8.18)	11.87 (8.63)	.86
Mean AB scores at T1	52.57	50.54	<.01
Mean AB scores at T2	48.72	44.88	<.01
Mean AB scores at T3	49.11	43.97	.17
Mean AB scores at T4	49.14	46.36	.05

<sup>a</sup> $p$  values < .05 indicate the variable is significantly related to data missingness

other variables in the study, it is reasonable to assume that the missing data mechanism was at minimum MAR.

### 3.2 Model Analyses

Five separate models were analyzed. The unconditional means model (Model 1) was used to identify the total variance in AB scores and partition this variance into between- and within-individual variation. The intra-class correlation (ICC), calculated as the proportion of the between-individual variance over the total variance, revealed that individual differences accounted for 51.6% of the total outcome variance.

In order to build subsequent growth models, the optimal growth function and level-1 error covariance structure needed to be specified. Three unconditional growth functions (linear, quadratic, cubic) were compared using likelihood ratio tests of model fit statistics. Individual change in AB over time was best represented by a cubic growth pattern,  $\chi^2(1)=10.37, p<.01$ . Homogeneous and heterogeneous level-1 error covariance structures were also compared, with the heterogeneous model yielding a statistically better fit,  $\chi^2(3)=25.35, p<.01$ . As a result, all subsequent growth models included a cubic growth pattern and were modeled using a heterogeneous level-1 error covariance structure. The quadratic and cubic effects of time were specified as fixed effects to achieve convergence in the estimation.

The unconditional growth model (Model 2) included a random linear effect of time and fixed quadratic and cubic effects. Results revealed an average AB trajectory for the sample characterized by a linear component of  $-1.50$ , a quadratic component of  $-.40$ , and a cubic component of  $-.03$ . A graphic representation of this trajectory is presented in Fig. 1. The variance for the linear growth component was statistically significant ( $p<.01$ ), indicating that participants differed significantly in their AB change over time.

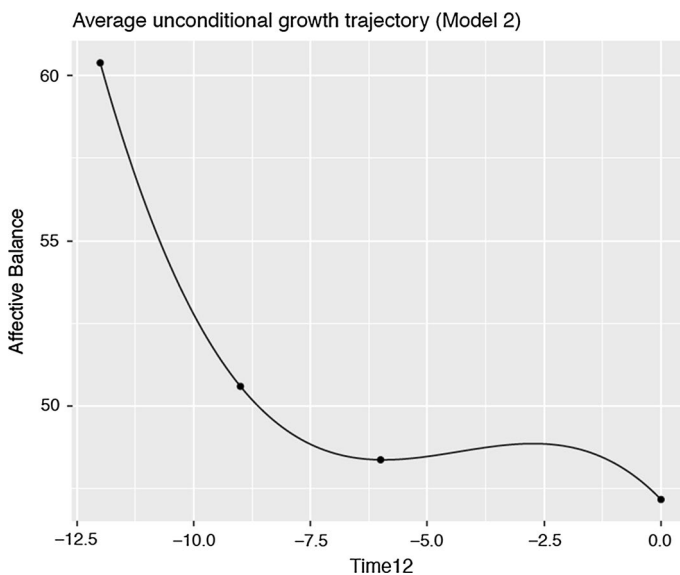


Fig. 1 Average unconditional growth trajectory for the sample

Two transitional models were used to identify which predictors to include in the final model. Model 3 included all demographic and injury-related variables as potential predictors of the random intercept (i.e., AB at 12 months) and the random linear effect of time (i.e., AB linear change rate over the 12 months). Education was the only significantly predictor of the random intercept [ $t(447)=2.70, p<.01$ ] and linear effect of time [ $t(447)=2.85, p<.01$ ], controlling for other demographic and injury-related variables. Notably, a positive mTBI diagnosis was not significantly predictive of AB at 12 months nor was it significantly associated with trajectory of AB over time. Consequently, this variable was removed from further analyses.

In Model 4, the four resilience and social support variables (i.e., resilience at Time1, social support at Time1, resilience change, and social support change) were tested as predictors of the random intercept and linear effect of time. Controlling for education; resilience at Time1 [ $t(195)=3.91, p<.01$ ], social support at Time1 [ $t(195)=2.43, p=.02$ ], resilience change [ $t(195)=4.94, p<.01$ ] and social support change [ $t(195)=4.07, p<.01$ ] all significantly predicted AB at 12 months. Resilience change [ $t(195)=3.32, p<.01$ ] and social support change [ $t(195)=2.52, p=.01$ ] significantly predicted the linear effect of time. Education, which no longer significantly predicted either the random intercept or linear effect of time, was removed.

The final model (Model 5) was the end result of preceding model testing procedures. Model 5 included a random intercept predicted by initial resilience (*RISILinC*), resilience change (*RISPerChgC*), initial social support (*SPSILinC*) and social support change (*SPSPerChgC*); a random linear effect of time (*Time12*) predicted by resilience change and social support change; and a fixed quadratic (*Time12Sq*) and cubic (*Time12Cb*) effect of time used to create the cubic growth function of AB. Results for the final model are presented in Table 3.

The average estimated AB score at Time4 (i.e., 12 months post-injury) was 49.27. This intercept was significantly predicted by resilience at Time1 [ $t(196)=5.76, p<.01$ ], resilience change [ $t(196)=5.39, p<.01$ ], social support at Time1 [ $t(196)=3.43, p<.01$ ] and

**Table 3** Results for the final model (Model 5)

Fixed effects	Parameter	Coefficient	Standard error	df	t ratio	p value
Intercept	$\beta_{00}$	49.27	.80	196	61.41	<.01
<i>RISILinC</i>	$\beta_{01}$	.25	.04	196	5.76	<.01
<i>RISPerChgC</i>	$\beta_{02}$	.27	.05	196	5.39	<.01
<i>SPSILinC</i>	$\beta_{03}$	.17	.05	196	3.43	<.01
<i>SPSPerChgC</i>	$\beta_{04}$	.27	.06	196	4.60	<.01
<i>Time12</i>	$\beta_{10}$	-1.44	.77	198	-1.88	.06
<i>RISPerChgC</i>	$\beta_{11}$	.01	.00	198	4.03	<.01
<i>SPSPerChgC</i>	$\beta_{12}$	.01	.00	198	3.30	<.01
<i>Time12Sq</i>	$\beta_{20}$	-.39	.17	349	-2.31	.02
<i>Time12Cb</i>	$\beta_{30}$	-.02	.01	349	-2.71	<.01
Random effects	Parameter	Variance component	Standard deviation	df	$\chi^2$	p value
Intercept	$\sigma_{r0}^2$	95.74	9.78	196	859.49	<.01
<i>Time12</i>	$\sigma_{r1}^2$	.17	.41	198	259.84	<.01

social support change,  $t(196)=4.60$ ,  $p<.01$ . Each of the four predictors positively predicted AB at Time4, controlling for the effects of the other three.

All growth components were negative, indicating that on average AB decreased over time. The significant fixed effects of the quadratic [ $t(349)=-2.31$ ,  $p=.02$ ] and cubic [ $t(349)=-2.71$ ,  $p\leq.01$ ] growth components indicated that there were significant changes in the growth rate of AB scores over the 12-month period. The statistically significant between-individual variation in the random linear growth component [ $\chi^2(198)=259.84$ ,  $p<.01$ ] suggests that individuals differed significantly in their AB trajectories.

The AB trajectories, which represent participants' unique change in AB over time, were significantly predicted by resilience change [ $t(198)=4.03$ ,  $p\leq.01$ ] and social support change [ $t(198)=3.30$ ,  $p\leq.01$ ], controlling for the effects of other variables in the model. Therefore, change in resilience and social support not only significantly predicted participants' AB at Time4 but also significantly predicted their changes in AB over the 12 months post-discharge. An increase in resilience was associated with an increase in the change rate of AB, and an increase in social support was associated with increased change rate of AB.

Pseudo- $R^2$  calculations revealed that the final model predicted 33.2% of the between-individual differences in AB scores at 12 months post-injury and 46.9% of the between-individual differences in the linear change rate in AB over time. As a supplement to the MLM modeling procedures, we tested the unique ability of the four resilience and social support variables to predict AB. For the variance in AB scores at 12 months post-injury, initial resilience uniquely explained 4.6%, initial social support explained 2.3%, resilience change explained 10.0%, and social support change explained 10.3%. For the variance in AB trajectory, initial resilience uniquely explained 9.4%, initial social support explained 3.2%, resilience change explained 31.3%, and social support change explained 21.9%.

## 4 Discussion

Affective balance (AB) in this heterogeneous sample of traumatically injured individuals followed a cubic growth trajectory characterized by decreasing scores at each measurement occasion over 12 months. The sharpest drop in AB occurred between initial measurement and 3 months post-discharge. Consistent with other larger studies of disability onset and SWB (Anusic et al. 2014; Lucas 2007; Oswald and Powdthavee 2008), traumatic injury appeared to initiate a significant and deleterious effect on AB that persisted throughout the year. Lacking pre-injury data and long-term assessments (> 1 year), our results cannot discount hedonic set-point models of adaptation, but they add to the growing literature documenting detrimental effects of traumatic injury on affective well-being, generally.

Our findings provide further evidence of the limited influence of "circumstantial" variables (e.g., demographic, injury-specific; Lyubomirsky et al. 2005) on AB following injury. Although the initial significant effects of education may imply greater access to resources that make it easier to cope during and after hospitalization, this association was negated when the measured psychological variables were entered into the models. Mild TBI diagnosed during hospitalization made no significant contribution to the models. A positive mTBI status was significantly associated with lower resilience at Time1, but no other meaningful patterns were observed unique to mTBI. The lack of effects uniquely attributable to mTBI may reflect the way in which the condition was diagnosed and recorded (which followed routine protocols for the trauma unit), and this may indicate more systematic approaches may be required to assess mTBI (including a history

of prior episodes of loss of consciousness, other TBIs, etc.) to further our understanding of the natural history of adjustment following emergency room treatment for an mTBI. However, there is no compelling evidence that negative emotional experiences are associated with a single incidence of mTBI in studies that feature appropriate control and comparison groups, and that consider the potential effects of other, non-mTBI factors (Rohling et al. 2017). Our findings indicate that the decreases observed in AB for the sample occurred following a traumatic injury, generally, and the factors that predicted the subsequent trajectories of AB occurred independent of mTBI status.

Overall, the results of the present study indicate that trajectories of AB in the months following traumatic injury may be best characterized by individual variability shaped by important psychosocial factors that convey differences in adaptability (and probable susceptibility to distress; Ormel et al. 2017, p. 121). Furthermore, the corresponding fluctuations in self-reported resilience and social support over time, and the relationship of the changes to AB, are indicative of a process that occurs in the wake of a traumatic injury that has a significant impact on AB. In the final model, initial resilience, resilience change, initial social support, and social support change significantly predicted AB 12 months post-discharge; and resilience change and social support change significantly predicted AB change over time. Together, these predictors explained 33.2% of the between-individual variance in AB 12 months post-discharge and 46.9% of the between-individual variance in AB change over time. Significant between-individual variability in the AB change over time remained even in the final model. Although resilience did not increase or decrease substantially for the sample when averaged together, meaningful changes, both positive and negative, occurred for individual participants. In other words, participants' self-reported resilience was notably influenced (for better or for worse) after traumatic injury. Furthermore, these changes in self-perceived resilience over time had a strong influence on AB, even when controlling for initial resilience scores. An increase in resilience was associated with an increase in AB change rate over time. Similarly, changes in social support over the 12-month period significantly predicted AB outcomes, even when controlling for initial social support scores. An increase in social support was associated with an increase in AB change rate over time.

We see two possible explanations of this dynamic interplay between resilience, social support, and AB in our results. The first concerns theoretical issues that may account, in part, for the relationships that presumably exist between resilience and social support, and how these mechanisms would then influence changes in AB. The second is less appealing in terms of theory, but it concerns empirical and measurement issues that should be entertained. Both perspectives have methodological and practical implications.

Converging evidence from studies of community and clinical samples indicates that resilient individuals exhibit proactive behaviors and report more adaptive, rewarding social relationships, more social support, and less interpersonal conflict than those who are not resilient (Dennissen et al. 2008; Elliott et al. 2017; Ong et al. 2009). Originally argued to reflect the social intelligence that accompanies ego resiliency (Block and Kremen 1996), it is also possible that the self-regulating abilities associated with resilience may also facilitate beneficial social and interpersonal exchanges (Gramzow et al. 2004). The association between resilience and close relationships certainly appears bi-directional: Increased contact and support from important interpersonal relationships is associated with resilience (Bonanno 2005), and rewarding social connections facilitate positive emotions that characterize resilience (Kok et al. 2013). This "positive cascade" of resilience, positive emotions, and social support is a reinforcing, motivating process that promotes social engagement,

personal confidence, and self-efficacy with understandable and measurable benefits to AB, specifically, and quality of life, generally.

From this perspective, individuals who are not resilient would likely have difficulty maintaining and engaging in important social and interpersonal relationships, and experiencing duress following traumatic injury, would exhibit behavioral problems that would undermine and tax relationships that could have been supportive. Lacking critical interpersonal skills and unable to regulate negative feelings of anxiety, frustration, anger, and sadness, individuals would experience declines in self-reported resilience as their perceived social support waned over time. Clinical interventions that address self-regulation and interpersonal skills may be indicated for these individuals in post-discharge plans to prevent this downward spiral in relationships and well-being (Diener et al. 2017) and in the process, promote social and interpersonal ties (Kok and Fredrickson 2014).

Yet this positive cascade may also reflect a tautology between these same constructs. On average, social support decreased over time for the sample, and although we do not know why this occurred, it is possible that relationships can be a source of considerable distress that, in turn, may affect self-reports of personal resilience and AB. It is also possible that the fairly transparent, “face valid” nature of the resilience measure render it susceptible to mood effects. The correlations between CD-RISC scores and measures of adjustment are consistently stronger in cross-sectional research. However, longitudinal research finds the measure accounts for very small amounts of variance in distress assessed a year later (1–2%; Silverman et al. 2015), and the predictive qualities of the CD-RISC total score are not significantly related to outcomes when stable personality traits and repeated measures of constructs are included in a contextual model that takes into account overlapping variance between the measures (Elliott et al. 2015). Finally, individuals who experienced increases in distress over time would surely report decreasing levels of AB that likely have, in turn, resulted in negative perceptions of personal resilience and available support. None of these possibilities can be ruled out in the present study.

The results of the current study provide evidence that AB generally declines after sustaining a traumatic injury. At the same time, significant variability in participants’ AB trajectories over the 1-year period was found. These findings raise doubts about models of hedonic adaptation, which propose that individuals who sustain a traumatic injury eventually adjust to their condition such that any loss in well-being eventually returns to pre-injury level. Our results highlight the importance of determining the degree of risk and possible need for psychosocial interventions among those hospitalized for traumatic injuries and who are likely to experience diminished quality of life following discharge. Our study confirms that self-perceived resilience and social support are strong predictors of AB 1 year post-injury. In addition, a decrease in one’s resilience and social support after the injury seems to predict a longitudinal decrease in AB over time, even when controlling for original resilience and social support scores. These results contribute to the growing body of literature that conceptualizes adjustment following traumatic disability as a dynamic process in which personal and social resources may facilitate or impede adjustment, depending on individual circumstances (Elliott et al. 2002; Martz et al. 2005).

#### 4.1 Limitations and Future Directions

Simultaneously testing a large number of variables, many of which were significantly correlated, may have affected the results. Individuals with greater resilience and social support at the beginning of the study likely had higher AB scores at the beginning as well,

potentially creating a ceiling effect whereby these individuals would have had less room for their AB scores to “improve” over time. Furthermore, the large number of demographic and injury-related variables may have reduced the potential power for any single variable to have a significant effect. It may also be that variables such as change/loss of employment after injury (as opposed to employment status at time of injury), functional independence and/or ability to participate in meaningful activities (as opposed to injury severity), and marital satisfaction (as opposed to marital status) would yield stronger effects on AB.

The study included individuals with traumatic injuries severe enough to warrant hospitalization, yet excluded individuals with the most severe injuries (ISS scores > 50). The results of this study can be generalized to individuals who sustain a similar severity of injury. The higher proportion of males and individuals who are unmarried and unemployed in the study may render the results less generalizable to females and those who are married and employed. The high rate of panel dropout limits generalizability of the findings. In general, problems observed with attrition and missing data in the present study reflect the difficulties encountered with samples recruited from a metropolitan trauma center that primarily serves a low-income, high-risk population.

Future longitudinal research should continue to employ statistical methods such as MLM to understand how individuals’ well-being outcomes change over time following traumatic injury. Studies of AB specifically would complement the existing literature concerning research on life satisfaction, providing a more comprehensive understanding of SWB outcomes. The most marked changes in AB appear to occur in the first few weeks or months post-injury, but longer measurement intervals (e.g., 5 or 10 years) would provide a clearer picture of whether and to what degree hedonic adaptation occurs. Long-term longitudinal data could be analyzed using a piecewise model, segmenting the trajectory into a “short-term” trajectory to capture the immediate changes in SWB and a “long-term” trajectory to capture more subtle changes likely to occur over longer periods of time (Raudenbush and Bryk 2002).

Although the current study included individual difference variables related to participants’ self, environment, and injury, future research should attempt to include factors which may mediate the relationships between these individual and socio-environmental factors and AB. Several models of health-related quality of life suggest that individual and socio-environmental factors influence outcomes through their effect on “process-linked” factors such as perception, appraisal, and coping that occur after a major life event (Bezner and Hunter 2001; Elliott et al. 2002; Martz et al. 2005). While reliable measurement of these process factors is challenging, their inclusion will likely provide a deeper understanding of mechanisms underlying changes in AB following traumatic injury. Clarifying the relationship between antecedent and process factors may be the next step in understanding *why* the changes in AB vary for certain people and under certain circumstances.

The clinical implications of this study are less clear. Typically, clinical services are contingent upon an informed assessment, but initial levels of self-reported resilience and social support accounted for small amounts of variance in AB trajectories following return to the community (9.4 and 3.2%, respectively), and changes observed in these variables—whether positive or negative—had stronger associations with subsequent levels of AB post-discharge. Consequently, baseline information indicative of individuals at risk for distress following discharge is lacking. Arguably, clinical levels of depression and anxiety provide de facto evidence that an individual is not “resilient,” and psychological services would then be indicated.

Importantly, the American College of Surgeons Committee on Trauma recommends routine screening for depression and posttraumatic stress symptoms among patients

admitted to trauma centers (American College of Surgeons 2014). Additionally, models of intervention that follow individuals from the time of hospitalization to discharge and into the community to reduce the impact of the psychological consequences of trauma in a stepped care model are being further explored (Zatzick et al. 2013). Although following a significant traumatic injury an individual may be more concerned about the medical aspect of their care and be less inclined to consider psychological services for their concerns, models using a stepped care approach may be able to intervene as psychological consequences from the trauma evolve, especially after hospital discharge. There is evidence that peer support programs are as effective as psychological interventions in preventing rehospitalizations and emergency room visits (among individuals with chronic mental health issues; Clarke et al. 2000). Similarly, “clubhouse” models of rehabilitation have also shown to “enhance personal empowerment” by fostering close, supportive relationships and self-efficacy (Vandiver et al. 1995). Positive behavioral supports and peer support programming appear to be strategic and cost-effective ways to serve individuals following discharge, assuming reliable contact can be maintained with individuals after they return to the community.

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