



# Developing Innovators: A Longitudinal Analysis Over Four College Years

Benjamin S. Selznick<sup>1\*</sup>, Matthew J. Mayhew<sup>2</sup>, Christa E. Winkler<sup>3</sup> and Eric T. McChesney<sup>1</sup>

<sup>1</sup> School of Strategic Leadership Studies, James Madison University, Harrisonburg, VA, United States, <sup>2</sup> College of Education and Human Ecology, The Ohio State University, Columbus, OH, United States, <sup>3</sup> Department of Educational Leadership, Mississippi State University, Starkville, MS, United States

The purpose of this study is to examine the influence of collegiate environments and experiences on students' development of innovation capacities over four years of college. Drawing on an interdisciplinary theoretical framework and reliable innovation measures, students from nine postsecondary institutions in North America were surveyed at three time points: first-year fall, first-year spring, and fourth-year spring. Data were comprehensively analyzed using a growth mixture modeling approach. Results suggest that being a transfer student and having sustained engagement with experiences that connect in-class and out-of-class learning were associated with a robust innovation growth trajectory over-and-above known covariates, including personality traits. Implications for research, theory, and practice are considered.

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### \*Correspondence:

Benjamin S. Selznick  
selznibs@jmu.edu

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## INTRODUCTION

An important current shaping postsecondary education over the last decade has been a focus on developing innovators – students and graduates able to effectively engage the process of generating and executing contextually beneficial new ideas (Wagner, 2012; Selznick and Mayhew, 2019). As institutions have increasingly recognized the benefits of developing students' innovation capacities – those skills and abilities needed to effectively engage innovation (Selznick and Mayhew, 2018) – practices have moved beyond traditional associations with entrepreneurship education (Nabi et al., 2017) toward more inclusive presentations. This shift has resulted in novel learning experiences that can be woven throughout the curriculum (Swayne et al., 2021), considerations for institutional transformation (Hall and Lulich, 2021), and the establishment of durable innovation networks (e.g., Thompson, 2018). Indeed, many institutions and their stakeholders now consider innovation an area that can satisfy many while alienating few: it fulfills students' demands for leveraging education for practical ends, achieves parents' and employers' demands for developing workforce-ready graduates, and addresses legislators' demands for demonstrating 21st century value (e.g., Swayne et al., 2021).

Despite benefits associated with developing innovators (Wagner, 2012), and the expansion of resources associated with achieving this outcome (e.g., Wyllie, 2018), limited attention has been paid to examining the longitudinal development of students as innovators across four years of undergraduate learning. Previous efforts have considered the measurement of innovation capacities (Selznick and Mayhew, 2018); their development during the first year of undergraduate study (Selznick and Mayhew, 2019); the associations between specific collegiate interventions and innovation capacities (Mayhew et al., 2012, 2016, 2019, 2021);

and the connection between students' innovation intentions and integrative learning (Selznick et al., 2021a). These studies have been limited by their time horizon, with research designs unable to address the influence of a longer undergraduate career on the development of innovation capacities.

In this study we address this limitation and ask: What collegiate environments and experiences influence the development of students' innovation capacities over four years of college? Utilizing growth mixture modeling (GMM; see Duncan et al., 1999) we identify latent classes within the data and test the extent to which development is related to pre-existing student characteristics and differential learning exposures.

## THEORETICAL FRAMEWORK

This study is framed by two theoretical perspectives: Kegan's (1994) lines of human development and ecological approaches to the study of college students. Kegan's (1994) theory of human development maintains that personal growth occurs along three interrelated and interdependent dimensions of the self: intrapersonal, social, and cognitive. The learning that propels development along these lines can be either informative or transformative in nature. Transformative learning involves "the development of a capacity for abstract thinking so that one can ask more general, thematic questions *about* the facts" (Kegan, 2009, p. 42). While informative learning is vital, transformative learning can unlock the shifts in perception, thinking, and doing often associated with innovation capacities (see Wagner, 2012; Swayne et al., 2019). This framework informs the measurement of innovation capacities comprising intrapersonal (e.g., motivation), social (e.g., teamwork across difference), and cognitive (e.g., creativity) dimensions as well as directing our inquiry toward transformative learning experiences.

Our examination of these experiences and the environments in which they are embedded draws upon ecological systems theory, specifically Bronfenbrenner's (1979; 1993) *chronosystem* and Renn and Arnold (2003) refinement of the concept. Ecological systems theory recognizes that students exist in a constant dynamic with actors, systems, policies, and historical legacies operating both within and beyond their immediate control. These systems and the individuals within them continuously vary over time, generating both organizational histories and trajectories of human development. These developmental trajectories differentiate according to an individual's immutable features (e.g., personality, race), and how students interact with the environmental systems around them (e.g., peer cultures, college experiences, academic integration, institutional conditions). Thus, ecological systems theory is a valuable guide to the explanation and interpretation of differential developmental trajectories due to person-environment interactions.

While our study does not and cannot explicitly consider all aspects of the ecologies that motivate or inhibit students' innovation capacity development, we draw on these considerations when building our latent class analyses with respect to pre-college characteristics which may shape growth

trajectories. We further draw on such approaches when modeling predictors of classification and growth (e.g., learning practices, academic pathways) associated with college-going.

## LITERATURE REVIEW

We reviewed an interdisciplinary body of literature covering individual and institutional factors associated with innovation to specify our growth mixture model. While not exhaustive, each set of perspectives addresses concepts and variables previously incorporated in the study of developing innovators during college (e.g., Morris et al., 2013).

### Individual Characteristics

While innovation can be taught (Mars and Rhoades, 2012; Bock et al., 2020), the possession of innate personality characteristics has also been consistently associated with more powerful development of innovation skillsets (Pittaway and Cope, 2007; Brandstätter, 2011). Specifically, meta-analyses and studies utilizing the big-five personality inventory have reported possessing higher levels of openness to new experiences (Kerr et al., 2017), conscientiousness, proactivity (Newman et al., 2019), extraversion, and agreeableness (Leutner et al., 2014) to be associated with greater innovation. Hence, our measurement instrument and analytic model both included variables measuring personality traits.

Considerable research suggests that gender plays an important role in predicting innovative and entrepreneurial outcomes due to systems of inequality and oppression that privilege patriarchal identities, values, and behaviors (Wilson et al., 2007). Cognitively, women and men may differ in how they perceive and process opportunities for innovation (DeTienne and Chandler, 2004, 2007) and women frequently exhibit less tolerance for risk (Shinnar et al., 2012), likely due to the disproportionate costs they may incur by failing. Regarding intrapersonal distinctions, women's entrepreneurial self-concept and self-efficacy appear to be affected by subtle messaging in their environments, resulting in disparities that are evident from an early age and that reduce the propensity of women to actually engage in innovation, even when they possess the skill and opportunity to do so (Langowitz and Minniti, 2007; Wilson et al., 2007). As such, it is vital to include gender in any approach to modeling innovation trajectories through college (see also Huang-Saad and Celis, 2017).

In addition, structures of oppression provide opportunities to members of some racial and ethnic groups while denying them to others in the innovation space (Fairlie, 2005). Theoretical approaches have considered innovation among BIPOC students through sociocultural lenses (Walker, 2009; Gold, 2016; Wingfield and Taylor, 2016) as being responsive to contexts which are the result of historical exclusions from equitable access to capital, innovation power structures, and inclusive policy. Undergraduate studies have demonstrated that racially minoritized students engage in the entrepreneurial co-curriculum as frequently as their White peers (Huang-Saad and Celis, 2017), and that they are equally or more

interested in becoming innovative entrepreneurs (Rodriguez et al., 2015; Gilmartin et al., 2019).

This study's model also includes two important predictors associated with family: first generation college student status and family history of innovation. First, ample research (e.g., Pascarella et al., 2004; Tate et al., 2015; Carpenter and Peña, 2017) demonstrates the salience of including first-generation student status in empirical attempts to understand the relationship between collegiate learning and outcomes given possible structural, financial, and sociocultural constraints experienced by these student populations (Davis, 2010). Second, research emerging from entrepreneurship studies (e.g., Schmitt-Rodermund, 2004; Marques et al., 2018) suggest the importance of considering family history with innovation and/or entrepreneurship when examining students' learning and development on these dimensions (Newman et al., 2019).

Finally, we included several predictors associated with students' academic profiles to consider students' emergent innovation capacities in the context of majors (Chopp et al., 2016), academic performance (Wagner, 2012), transfer status (Johnson, 2005), and international student presentations (see Moriano et al., 2012). Given previous approaches to this topic, this study was particularly attuned to the extent to which innovation capacity development was associated with major (e.g., business, engineering) and whether there could be a connection between transfer and innovation capacities along developmental dimensions (see Lukszo and Hayes, 2020).

## Learning Experiences

In addition to summative examinations of how colleges can generate organizational identities that foster innovative campus climates (see Morris et al., 2017), multidisciplinary literature has considered the extent to which curricular and co-curricular experiences can promote undergraduate innovation. Studies of innovation-specific learning (Martín et al., 2017; McCarthy et al., 2018) and its possible associations with campus-wide entrepreneurship education (Nabi et al., 2017; Passaro et al., 2018) indicate that curricular experiences can support students' innovation capacity development. Beneficial pedagogical elements include high-quality faculty teaching, active collaboration (Loes, 2019), experiential learning (Mason and Arshed, 2013), and opportunity identification (Corbett, 2005).

Studies of co-curricular experiences (e.g., Selznick et al., 2021a), have illuminated the benefits of *integrative learning*, or learning that connects student identities, classroom knowledge, and out-of-class experiences (e.g., across knowledge domains, social environments, etc.) in new ways. Additionally, engaging with student associations (Padilla-Angulo, 2019) and long-term career development (Lange et al., 2011) have been identified as positive contributors to innovation capacity development. As Walter and Lankes (2015) observe with respect to libraries: "Innovation may involve collaboration with student affairs professionals to consider the impact of co-curricular spaces on student learning" (p. 855). Motivated by this literature review, we incorporated aspects of students' perceptions of their curricular (e.g., faculty challenge) and co-curricular (e.g.,

connecting experiences) experiences associated with innovation into our survey and subsequent quantitative model.

## MATERIALS AND METHODS

This study used quantitative data collected via an established survey of college students' innovation capacities (Selznick and Mayhew, 2018). Using survey data collected at three different timepoints during college, longitudinal analyses were conducted to evaluate trends and predictors of students' change in innovation capacities over time.

### Participants

College students were sampled at 9 institutions, which were recruited to participate on the basis of their demonstrated interest in the project. The analytic sample included all students who responded to at least two of the three timepoints ( $N = 572$ ) in order to protect the integrity of the longitudinal analysis. Descriptive statistics for all variables are reported in **Table 1**. Given the lack of a definable set of respondent characteristics associated with missingness, data were treated as missing at random (MAR). Full information maximum likelihood (FIML) estimation was then used to handle cases of missing data as it allows for utilization of all available data points, while maintaining the accuracy and integrity of model parameters (Wothke, 2000).

### Procedure

The survey was administered electronically at three timepoints. Students were initially surveyed as first-year college students in the fall of 2015 (Time 1). The second administration occurred in the spring of 2016 (Time 2). The third administration occurred in the spring of 2019 (Time 3).

### Survey Instrument

The instrument employed was the Innovation Capacities Scale developed by Selznick and Mayhew (2018) to evaluate students' innovation capacities as a higher education outcome. The internal structure of the scale and subscales demonstrated strong unidimensionality as evinced by Cronbach's  $\alpha$  values above 0.7 (Cronbach, 1951; DeVellis, 2016). The scale included 42 survey items capturing nine innovation capacities: intention to innovate ( $\alpha = 0.78$ ), self-concept ( $\alpha = 0.80$ ), creative cognition ( $\alpha = 0.86$ ), proactivity ( $\alpha = 0.81$ ), persuasive communication ( $\alpha = 0.84$ ), risk taking ( $\alpha = 0.85$ ), teamwork ( $\alpha = 0.83$ ), motivation ( $\alpha = 0.72$ ), and networking ( $\alpha = 0.85$ ). Using second-order confirmatory factor analysis (Rindskopf and Rose, 1988; Selznick and Mayhew, 2018) demonstrated the robust fit of their model, and established criterion validity with a sample of 1,379 first-year college students at six North American institutions. All nine innovation capacities were first-order factors comprising one higher-order factor: innovation capacity ( $\alpha = 0.94$ ). To account for the known influence of personality traits (Chell, 2008), the instrument also included the Ten Item Personality Inventory (TIPI; Gosling et al., 2003), a valid and reliable measure of the Big Five personality traits (Costa and McCrae, 1992).

**TABLE 1** | Variable descriptives for analytic sample ( $N = 572$ ).

	Mean	S.D.	Min.	Max.
<b>Personality</b>				
Extroversion	-0.11	0.99	-1.88	1.92
Conscientiousness	0.06	0.99	-3.69	1.30
Neuroticism	-0.02	0.98	-2.70	1.65
Openness	-0.03	1.02	-2.65	1.51
Agreeableness	0.04	1.03	-3.40	1.88
<b>Gender Identity</b>				
Man	0.42	0.49	0.00	1.00
Woman	0.56	0.50	0.00	1.00
Another gender identity	0.01	0.09	0.00	1.00
Prefer not to answer	0.01	0.12	0.00	1.00
<b>Race/Ethnicity</b>				
African American/Black	0.03	0.17	0.00	1.00
Asian American/Asian	0.23	0.42	0.00	1.00
Hispanic or Latino	0.04	0.20	0.00	1.00
Middle Eastern/North African	0.01	0.08	0.00	1.00
Native American/Alaska Native	0.00	0.04	0.00	1.00
Native Hawaiian/Pacific Islander	0.00	0.04	0.00	1.00
White/Caucasian	0.60	0.49	0.00	1.00
Another race/ethnicity	0.02	0.13	0.00	1.00
More than one race	0.07	0.26	0.00	1.00
First-generation	0.77	0.42	0.00	1.00
Family business	0.41	0.49	0.00	1.00
Family innovator	0.20	0.40	0.00	1.00
High school GPA	-0.13	0.92	-0.90	4.44
<b>Major</b>				
Arts	0.06	0.23	0.00	1.00
Humanities	0.03	0.18	0.00	1.00
Business	0.24	0.42	0.00	1.00
Education	0.04	0.21	0.00	1.00
Social sciences	0.07	0.25	0.00	1.00
Health professions	0.07	0.26	0.00	1.00
Engineering	0.11	0.32	0.00	1.00
Computer science	0.03	0.18	0.00	1.00
Biological sciences	0.10	0.30	0.00	1.00
Math/Statistics	0.04	0.19	0.00	1.00
Physical sciences	0.03	0.18	0.00	1.00
Undecided	0.06	0.24	0.00	1.00
Double major	0.08	0.26	0.00	1.00
Other major	0.04	0.20	0.00	1.00
Transfer student	0.06	0.23	0.00	1.00
International student	0.13	0.33	0.00	1.00
Innovation course taker	0.14	0.35	0.00	1.00
<b>Curricular experiences</b>				
Faculty challenge	-0.03	1.03	-3.45	1.74
Faculty interaction	-0.02	1.03	-3.15	1.08
Assessments: Argument develop	0.01	1.00	-3.00	2.02
Assessments: Innovative Problem Solving	-0.02	1.00	-3.33	1.92
<b>Co-curricular experiences</b>				
Connecting experiences	0.02	1.00	-2.93	1.23
Social experiences	-0.02	1.02	-4.04	1.33
Campus encouragement	-0.02	1.00	-3.45	2.09
Career development support	-0.02	1.02	-3.84	1.97

## Measures

The same framework and measures used by Selznick and Mayhew (2019) were applied in the current study. Specifically, innovation capacities factor scores were the outcome measure; composite scores for students' various curricular and co-curricular experiences were used as environmental measures; survey items capturing student demographics and precollege characteristics were used as input measures; and student attributes related to the college environment were used as bridge measures.

### Outcome Measure

The outcome measure was derived from that established by Selznick and Mayhew (2018). Specifically, factor scores computed from the second-order innovation capacities factor were used as the outcome of interest. Factor scores were computed via Mplus software employing the regression-based maximum *a posteriori* method (Muthén and Muthén, 1998/2017). Factor scores were converted to a 100-point scale, with 0 indicating the lowest possible innovation capacity and 100 indicating highest possible innovation capacity to assist result interpretation.

### Input Measures

The model included twelve variables accounting for students' demographic and pre-college characteristics. Specifically, these comprised measurements of the "big five" personality characteristics (extroversion, conscientiousness, neuroticism, openness, and agreeableness; Gosling et al., 2003), alongside their gender identity, their race/ethnicity, their high school grade point average (GPA), whether or not they were first generation students, whether or not they possessed a family member who started a new business or non-profit (family business), or possessed a family member who invented a new product, service, or process (family innovator). First generation status, family business, and family innovator were dummy coded.

### Bridge Measures

Bridge measures are characteristics inherent to an individual, but that primarily exist within the college context (Astin, 1991). In the present model, these included students' college major, whether or not they were an international student, and whether or not they had taken any courses in entrepreneurship, creativity, or innovation (innovation course taker), with these last two variables being dummy coded.

### Environmental Measures

Drawing on measures initially developed as part of the Wabash National Survey (WNS; e.g., Pascarella et al., 2004, 2005), and continued in previous efforts in this line of research (e.g., Selznick, 2017), the model included eight composite environmental measures divided evenly between those measuring curricular and co-curricular experiences. These were gathered at Times 2 and 3. The curricular measures evaluated the degree to which faculty challenged them to think in new and original ways (faculty challenge,  $\alpha = 0.83$ ), the frequency and quality of their interactions with faculty members (faculty interaction,  $\alpha = 0.80$ ), how often they

experienced assessments that required the development and defense of arguments (assessments: argument development,  $\alpha = 0.80$ ), and how frequently they experienced assessments that encouraged innovative problem solving (assessments: innovation problem solving,  $\alpha = 0.71$ ). The co-curricular measures evaluated how often participants were able to connect extracurricular experiences to in-class learning (connecting experiences,  $\alpha = 0.88$ ), how frequently they had social experiences that encouraged innovation (social experiences,  $\alpha = 0.89$ ), how encouraging of innovation they experienced the campus to be (campus encouragement,  $\alpha = 0.87$ ), and how deeply the campus supported their career development (career development support,  $\alpha = 0.74$ ).<sup>1</sup> Each of these composite measures were standardized before entry.

## Analyses

This study used growth mixture modeling, or GMM (Muthén, 2004) within a structural equation modeling (SEM) framework in order to quantify longitudinal changes in students' innovation capacities scores. All analyses were executed using Mplus (Muthén and Muthén, 1998/2017). Traditional growth models assume that the sample represents a single population that can be accurately characterized by one growth trajectory; GMM, however, relaxes that assumption and allows for the possibility that the sample includes multiple distinct subgroups, or "classes," of individuals, with each subgroup characterized by its own separate change trajectory (Jung and Wickrama, 2008; Shiyko et al., 2012). It thus produces separate growth estimates for each subgroup inferred from the data, making it "naturally suited" for addressing person-centered research questions pertaining to longitudinal development (Diallo et al., 2017, p. 166).

In accordance with the methodological literature (e.g., Muthén, 2004; Grimm et al., 2017), our growth mixture modeling analysis included multiple steps: (1) identification of latent classes based on both statistical and theoretical considerations, (2) examination of developmental trajectories based on estimated growth parameters, and (3) prediction of class membership via incorporation of input and environmental measures.

### Class Enumeration

The class enumeration process—or identification of the number of latent classes present in a dataset—is determined by a combination of factors including statistical fit indices, substantive theoretical justifications, and the interpretability of the latent classes (Muthén, 2004; Nylund et al., 2007). To begin the class enumeration process a one-class model was established as the baseline; this one-class model assumed that development was homogeneous across all students, and thus was fully captured by a single growth trajectory (Shiyko et al., 2012). Alternatively, models with  $n$  latent classes allow for the possibility that there are  $n$  distinct trajectories in students' change in innovation capacities during college. If such a model offers an improvement over the baseline model, then it can be concluded that there are multiple ( $n$ ) different developmental trajectories in students'

<sup>1</sup>Full item presentation and psychometric information can be found in Selznick and Mayhew (2019).

change in innovation capacities during college (Shiyko et al., 2012)—trajectories which are sufficiently distinct to warrant modeling separately.

Thus, using the innovation capacities outcome, models comprised of one, two, and three latent classes were estimated and evaluated. Comparative indicators of global model fit were used to guide the GMM class enumeration process. Those indicators included the Bayesian Information Criterion (BIC), sample-size Adjusted Bayesian Information Criterion (ABIC), and Akaike Information Criterion (AIC). In these indicators a lower value indicates a better fitting model. The Lo et al. (2001) Likelihood Ratio Test (LMR-LRT), Vuong, Lo, Mendell, and Rubin Adjusted Likelihood Ratio Test (VLMR), and Bootstrap Likelihood Ratio Test (BLRT) were also used to compare nested models. The LMR-LRT, VLMR, and BLRT are alternatives to the likelihood ratio test whereby a significant value suggests that an estimated model with  $K$  classes is superior to a model with  $K-1$  classes.

### Growth Trajectories

Once the number of classes inferred from the data was established based on statistical fit, relevant theory, and model interpretability, growth trajectories for each identified subgroup were examined. In order to understand the trends of each identified subgroup, each class received its own unique estimate of the mean intercept and mean slope for innovation capacities. The mean intercept reflects students' baseline innovation capacities at Time 1, and the mean slope reflects the magnitude and direction of change in students' innovation capacities at Times 2 and 3. For both the intercept and slope, a significant value indicates that the estimate is significantly different from zero. Of particular interest in this study was the slope, as it serves as an indicator of whether students' innovation capacities increased (or declined) in any significant ways during their time in college. The growth trajectory for each latent class was then modeled via a simple equation in which  $Outcome = Intercept + Slope(Time)$ .

For this final model, entropy was also evaluated as a measure of classification quality, or how distinguishable the classes and their associated trajectories were from one another. Entropy values range from a low of 0 (i.e., not distinguishable) to a high of 1 (i.e., very distinguishable) (Grimm et al., 2017).

### Growth Predictors

In order to evaluate which factors are most influential in promoting students' development of innovation capacities in college, significant predictors of the growth trajectories were examined. Input, environmental, and bridge variables consistent with those presented by Selznick and Mayhew (2019) were incorporated into the GMM to evaluate which variables predicted students' class membership. A manual three-step approach (Vermunt, 2010) was used. This approach did not treat students' class membership as a perfectly reliable indicator; instead, it used the probabilities of class membership from the original unconditional GMM (step 1) to estimate the error in students' classification (step 2), and then account for that error in the conditional predictor model (step 3) (Asparouhov and Muthén, 2014; Nylund-Gibson et al., 2019).

Consistent with the GMM framework, rather than assuming uniform influence across the sample, the influence of covariates was estimated separately for each latent class. The ability of covariates to predict class membership in GMMs was described via multinomial logistic regression parameters (Petras and Masyn, 2010). The resulting estimates were odds ratios, which indicated the likelihood of particular individuals having membership in one class compared to a reference class. To aid interpretation, odds ratios were also converted to probabilities.

### Limitations

This study has several important limitations. First, the institutional sample for this study is not representative of the full scope of postsecondary institutions. Subsequently, the students who self-selected into these institutions and into our sample via participation in the survey at multiple time points may not be fully representative of the diversity comprising postsecondary attendees. Resultantly, we make no claims of universal generalizability for our findings, instead recognizing that, despite the quality of our longitudinal data and rigor of our analysis, we can only forward suggestive, not definitive results.

Additionally, scholars (Bauer and Curran, 2003a,b; Bauer, 2007) have noted that GMM analyses can over-extract substantively meaningful classes and/or trajectories under some conditions. Furthermore, GMM's can sometimes become stuck at local maxima, producing results that do not match the solution of the global maximum likelihood function (Hipp and Bauer, 2006). We thus urge a degree of caution and remind that the results of this study aim to provide a carefully conducted, if inherently probabilistic, empirical picture of latent classes, growth pathways, and predictors. Such findings are not meant to be end-point statements on these matters, but rather, evidence that is subject to further testing within collegiate contexts.

## RESULTS

### Class Enumeration

The class enumeration process included estimating and examining fit for the one-, two-, and three-class innovation capacities models. Evaluation of model fit criteria provided consistent evidence that the two-class model was a better fit than the one-class model, exhibiting lower AIC, BIC, and ABIC values and significant LMR and VLMR tests. While the AIC, BIC, and ABIC values were lower for the three-class model than the two-class model, the LMR and VLMR tests were non-significant, indicating that the three-class model did not provide a better fit to the data than the two-class model. Furthermore, the third class comprised only 1.5% of the sample, (i.e., less than 10 students). Any class consisting of such a small proportion of the sample is likely to be the result of sample-specific trends or overextraction, rather than representing meaningful differences in the larger population.

Statistical model fit indices used for comparison of the one-, two-, and three-class models are summarized in **Table 2**. Ultimately, evaluation of model fit criteria indicated that the two-class model fit the data best. In other words, there was sufficient

**TABLE 2** | Model fit of 1-, 2-, and 3-class innovation capacities models for class enumeration.

	LL	AIC	BIC	ABIC	LMR		VLMR		BLRT		Smallest Proportion
					Est	p-value	Est	p-value	Est	p-value	
1-Class Model	-4958.403	9932.806	9967.599	9942.203	—	—	—	—	—	—	—
2-Class Model	-4933.694	9889.388	9937.228	9902.308	46.953	0.013	-4958.403	0.011	-4958.403	0.000	0.132
3-Class Model	-4914.338	9854.677	9911.215	9869.946	39.233	0.201	-4934.984	0.191	-4934.984	0.000	0.015

LL = Log-likelihood value; AIC = Akaike information criteria; BIC = Bayesian information criteria; ABIC = Sample size adjusted BIC; LMR = Lo-Mendell-Rubin likelihood ratio test; VLMR = Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test; BLRT = Parametric bootstrapped likelihood ratio test.

**TABLE 3** | Growth parameters from 2-class innovation capacities model.

	%	Intercept			Slope		
		Est.	S.E.	p-value	Est.	S.E.	p-value
Class 1	86.8	52.605***	0.803	0.000	-0.592	0.533	0.422
Class 2	13.2	75.090***	3.418	0.000	7.449*	2.997	0.014

\*\*\* $p < 0.001$ ; \*\* $p < 0.005$  \* $p < 0.05$ .

heterogeneity in students' growth trajectories for multiclass modeling and that heterogeneity was best captured by two separate latent classes. Accordingly, all subsequent analyses were conducted using the two-class GMM.

## Growth Trajectories

The 2-class model revealed distinct patterns of students' change in innovation capacities over the three timepoints. **Table 3** reports initial values (i.e., intercept) and average change over time (i.e., slope) by class. As depicted in **Figure 1**, the two classes included a no growth trajectory (class 1, 87% of the sample) and a high growth trajectory (class 2, 13% of the sample). Students in class 1 started their first year of college with moderate innovation capacities (intercept = 52.605,  $p < 0.001$ ) and experienced no significant change in those capacities at subsequent timepoints (slope = -0.592,  $p = 0.422$ ). Contrarily, students in class 2 started their first year of college with moderate innovation capacities (i.e., though they were slightly higher than those of class 1; intercept = 75.090,  $p < 0.001$ ) and experienced significant positive growth in those capacities during their time in college (i.e., slope = 7.449,  $p = 0.014$ ). An entropy value of 0.790 suggests that the resulting two classes were sufficiently distinguishable from one another.

## Growth Predictors

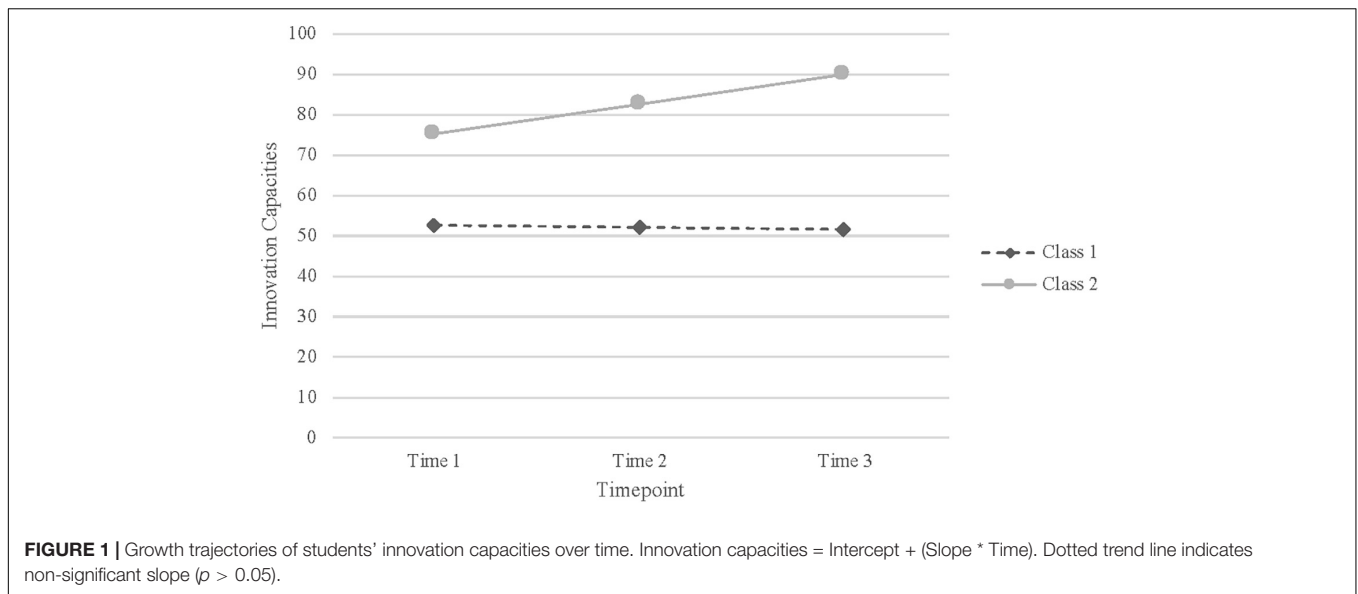
After establishing the growth trajectories for the 2-class GMM, the input, bridge, and environmental variables were added to the model to determine what characteristics or experiences predicted growth during college. The results, which were obtained using multinomial logistic regression, are reported in **Table 4** with class 1 (the class with no significant growth) as the reference group and class 2 (the class demonstrating significant growth) as the focal group. Five significant predictors emerged: extroversion, conscientiousness, openness, transfer student status, and connecting experiences.

Input variables capturing students' self-reported personality characteristics and transfer status significantly predicted growth in their innovation capacities. Students who reported higher extroversion had a 73.9% probability (odds ratio [OR] = 2.833; Probability [P] = 0.739;  $p$ -value [ $p$ ] < 0.001) of belonging to the growth class. Students who reported higher conscientiousness had a 66.0% probability (OR = 1.938; P = 0.660;  $p = 0.008$ ) of experiencing growth in innovation capacities. Students who reported higher openness had a 72.3% probability (OR = 2.604; P = 0.723;  $p < 0.001$ ) of experiencing growth in innovation capacities. Additionally, students who reported that they transferred from another university had a 77.5% probability (OR = 3.448; P = 0.775;  $p = 0.008$ ) of being in class 2.

One environmental/experiential variable significantly predicted class membership: connecting experiences. At time 3, students who reported having greater exposure to out-of-class experiences that had a positive influence on personal growth, attitudes, and values or that provided opportunities to translate knowledge and understanding from the classroom into action were significantly more likely to be in the growth class. Specifically, students who reported such connecting experiences had 90.2% probability (OR = 9.174; P = 0.902;  $p < 0.001$ ) of developing their innovation capacities.

## DISCUSSION

Results suggest that while several individual personality traits were significant predictors of innovation capacity development, the more powerful predictors of who developed as an innovator and who did not are what experiences students have in college. Specifically, high exposure to connecting experiences and being a transfer student were both statistically and practically significant predictors of belonging to the 13% of the sample that experienced a growth trajectory over four years of college. These findings potentially indicate pathways for stimulating the development of innovators and, ideally,



**TABLE 4 |** Multinomial logistic regression results for predictors of membership in class 2.

	Odds Ratio	S.E.	Probability	Sig
<b>Personality</b>				
Extroversion	2.833	0.120	0.739	***
Conscientiousness	1.938	0.181	0.660	*
Neuroticism	1.504	0.181	0.601	
Openness	2.604	0.141	0.723	***
Agreeableness	1.248	0.198	0.555	
Gender identity	0.181	3.350	0.153	
Race/Ethnicity	0.840	0.103	0.457	
First-generation	0.964	0.491	0.491	
Family business	0.271	3.365	0.213	
Family innovator	1.739	1.033	0.635	
High school GPA	0.826	0.437	0.452	
Major	0.978	0.058	0.495	
Transfer student	3.448	0.267	0.775	*
International student	0.480	1.522	0.324	
Innovation course taker	1.577	0.579	0.612	
<b>Curricular experiences</b>				
Faculty challenge	1.433	0.495	0.589	
Faculty interaction	0.695	0.511	0.410	
Assessments: Argument develop	0.741	0.701	0.426	
Assessments: Innovative problem solving	0.952	0.683	0.488	
<b>Co-curricular experiences</b>				
Connecting experiences	9.174	0.078	0.902	***
Social experiences	0.428	1.421	0.300	
Campus encouragement	0.879	0.778	0.468	
Career development support	0.531	0.698	0.347	

Class 1 used as reference group. Probability computed as Odds Ratio/(1 + Odds Ratio). \*\*\* $p < 0.001$ ; \*\* $p < 0.005$  \* $p < 0.05$ .

coming to expand such development for an increasing number of undergraduate students.

The powerful association between connecting experiences and innovation capacity growth suggests that what happens outside of class – the myriad forms of intrapersonal, social, and cognitive development that are essential to providing a

truly holistic postsecondary education – aren't incidental or detrimental to student learning, but integral and central. In fact, it may be the case that time out of class is where the translation and application of new knowledge into contextually beneficial action must occur. This finding further supports the developmental benefits of applied learning, that is, approaches



anchored in activity, collaboration, and integrating knowledge which may provide opportunities for transformation (Trolian and Jach, 2019). Moving forward, we suggest that traditional ‘sage-on-the-stage’ college learning may be limiting students’ innovation capacity development by systematically failing to ignite undergraduates’ active quests toward producing new ideas (Cavagnaro and Fasihuddin, 2016).

The finding regarding transfer student status predicting high development may indicate both individual and institutional lines of influence. Individually, the act of transferring may stimulate innovative coping (Anglin et al., 1995). Students who choose to transfer need to accept potential personal, social, and financial risks; be comfortable with quitting and starting anew; must possess intrinsic motivation and navigational capital to persist across institutional systems; and might need to be persuasive in their communication and proactive in establishing new social networks (Johnson, 2005). They may have also learned an important mindset for innovation – that there are what Dubner (2011) terms “upsides of quitting”. At the institutional level, this finding presents evidence that some students may transfer not because something is “wrong with them” but, instead, because the institution is not supporting their educational needs. Further, and in line with our previous findings (Selznick et al., 2021b), it is possible to create a campus climate and reputation for innovation. Therefore, students who transferred into the institutions in our sample may have done so because these institutions were known to provide supportive innovation environments.

While interpreting non-significant findings entails certain caveats (Field, 2017), no gender, race/ethnicity, major, or familial background predicted inclusion in the growth class. Such results in the presence of other significant predictors – most notably connecting experiences – indicate that such characteristics do not predetermine longitudinal innovation capacity development. This suggests that colleges can not only develop innovators, but can do so in ways that support diversity, equity, and inclusivity regarding *who* is deemed an innovator, in what contexts, and through what means (Hamilton, 2020).

Interpreting findings comprehensively through the lens of our theoretical framework, we contend that developing innovators is perhaps more ecological than idiosyncratic in nature (Wagner, 2012; Swayne et al., 2019). Specifically, college ecologies that prioritize the integration and sustained application of learning throughout the continuous experiences of class, co-curricular involvement, community engagement, friendships, and pre-college relationships appear to promote innovation; those which impose artificial discretization and do not encourage knowledge application seem less effective. Or, building on Kegan (1994), approaches that foster transformational learning contribute to multidimensional growth and innovative development, while approaches restricted to informational learning do not.

## Implications

We now turn to considerations of our findings for theory, research, and practice. Regarding theory, our findings are broadly in line with Kegan’s (1994) proposed mechanisms

of college student learning. As he observes: “Educators seeking ‘self-direction’ from the adult students...are asking many of them to change the whole way they understand themselves, their world, and the relationship between the two” (Kegan, 1994, p. 275). This suggests higher education for innovation can come to be a place of *un-learning* (Battilana et al., 2019; Selznick and McCarthy, 2020) and that such applied (un)learning may overcome personality differentials and lead to more effective innovation capacity development.

Concerning ecological systems theory, our findings suggest that collegiate environments are perhaps more fluid than discrete in their manifestations and receptions by students. This consideration appears with respect to transfer students who leave one collegiate ecology in search of another; the importance of a sustained commitment to high-quality and intentional connecting experiences; the mechanisms that can support developing certain personality types as innovators; and even those climates that support developing innovators across genders, race/ethnicities, and family backgrounds. Recent work by Winks et al. (2020) further invites consideration of the importance of physical spaces and their associated cultures as key features of learning ecologies.

These findings suggest several new directions for research. First, future work should investigate connecting experiences to uncover where they are occurring in the ecology, amongst which student sub-cultures, and how precisely they stimulate innovation capacity development. Second, our findings should motivate more comprehensive studies of the distinctive postsecondary trajectories of transfer students (Lukszo and Hayes, 2020), including those who transfer from two- to four-year institutions and those who transfer among four-year institutions (Renn and Reason, 2013). Transfer students are at best under-studied and, at worst given the tuition-driven, marketized nature of postsecondary education (Taylor and Cantwell, 2019), blamed. Finally, and echoing our previous work (Mayhew et al., 2016), we suggest future researchers attempting to build comprehensive regression models consider the role of personality traits in influencing student behavior and outcomes.

Our considerations for practice concentrate on connecting experiences given their magnitude in our multinomial regression analysis. Guidance for contemporary employment of these practices is widespread, often focusing on forms of problem-based learning (Youngerman and Culver, 2019), collaborative learning (Loes, 2019), and/or transdisciplinary collaborations that bring students together and integrate their disciplinary insights to address complex societal issues (Heinrich et al., 2021). As indicated by ecological systems theory, the structured delivery of such experiences and subsequent student meaning-making must be an institutionally-supported priority, which empowers educators to establish integrative learning contexts (McCarthy et al., 2018; Barber, 2020). In short, if the pathway to developing innovators over-and-above personality traits or transferring lies in these experiences, they must be actively and

intentionally promoted through close collaborations between academic, student life, and policy stakeholders.

## CONCLUSION

While innovators may be born as a function of personality traits, findings from this study suggest they can also be developed through college experiences, regardless of family background, gender identification, or race/ethnicity. Given the complex challenges facing the 21st century, colleges must carefully consider how learning practices and environments proactively support students' innovation capacity building – especially as this outcome is sought after by contemporary undergraduates and increasingly reflected in strategic plans. An emphasis on innovation, moreover, may have effects well beyond college and help ensure that postsecondary graduates confidently enter a world where fresh ideas and novel solutions are desperately needed.

## DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

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## ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Institutional Review Board The Ohio State University. The patients/participants provided their written informed consent to participate in this study.

## AUTHOR CONTRIBUTIONS

BS contributed to the introduction, literature review, findings, and discussion. MM contributed to the introduction, findings, and discussion. CW contributed to the methods, findings, and discussion. EM contributed to the introduction, literature review, and discussion. All authors contributed to the article and approved the submitted version.

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