Research in Higher Education (2020) 61:1027–1053
https://doi.org/10.1007/s11162-019-09583-7

Shifting Gears: Characteristics and Consequences of Latent Class Transitions in Doctoral Socialization

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Received: 5 January 2019 / Published online: 28 October 2019

Abstract
Using a national sample of 336 biology Ph.D. students, this study classified students based on their interactions with faculty and peers, and investigated longitudinal changes in their interaction classifications over 3 years. We also examined associations between students' interaction classifications, their demographic backgrounds (e.g., gender, international student status, first-generation status, and underrepresented racial/ethnic minority status), and doctoral outcomes (e.g., sense of belonging, satisfaction with academic development, institutional commitment, and scholarly productivity). The findings revealed that three distinct subgroups existed among the current sample of biology Ph.D. students, with respect to their interactions with their faculty and peers: high interaction with faculty and peers, high interaction with peers only, and low interaction with faculty and peers. However, such patterns of doctoral students' interactions with faculty and peers tended to, in general, be stable over time. In addition, while the differential effects of demographic variables on changes in these interaction patterns were widely founded, such changes were not substantially linked to doctoral student outcomes. Implications for research on doctoral education and socialization theory are discussed.

Keywords Doctoral socialization · Faculty-student interaction · Peer interaction · Person-centered approach · Latent transition analysis

Introduction

Doctoral students' interactions with faculty and peers are critical components of the socialization process during their doctoral training (Flores-Scott and Nerad 2012; Gardner 2010a; Littlefield et al. 2015; Weidman and Stein 2003). Unfortunately, prior research has documented inequities in students' socialization experiences. For example, students of color less frequently report respectful relationships with their advisors relative to their

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white counterparts (Johnson-Bailey et al. 2009). First-generation doctoral students report experiencing disadvantages in terms of various aspects of socialization experiences compared to their peers with college educated parents (Gardner and Holley 2011). Other literature documents gender inequities in how students are socialized into masculinized disciplinary contexts (Sallee 2011). Likewise, inequities persist in the levels of advisor support reported by international students compared to their domestic peers (Curtin et al. 2013; Roksa et al. 2018).

Attending to inequities in these socialization experiences is imperative, given the theorized importance of faculty and peer socialization in determining academic and professional outcomes (Austin 2002; Weidman et al. 2001). Interactions with both faculty and peers may be especially important for students in laboratory-based sciences, as their learning and research activities take place within supervised laboratory research teams (Cumming 2009). Such socialization changes from year to year, both in relation to normative transitions between stages (i.e., anticipatory, formal, informal, personal; Weidman et al. 2001) and as a function of the structural characteristics of the doctoral program and laboratory environment. Thus, longitudinal investigations are especially useful in understanding how socialization influences doctoral students' abilities to become increasingly independent over time as they take on different roles and responsibilities throughout their graduate program (Austin 2002; Gardner 2010b; Lovitts 2005).

This article explores how patterns in peer and faculty interactions change over time with attention to differences by gender, international student status, first-generation status, and underrepresented racial/ethnic minority (URM) status. Using a sample of 336 cellular and molecular biology Ph.D. students in the United States, this study classifies students based on their interactions with faculty and peers, investigates changes in their interaction classifications over time, and examines associations between students' interaction classifications, their demographic backgrounds, and outcome variables expected to be influenced by their socialization processes.

The Importance of Faculty and Peer Interactions

The important role of departmental faculty—especially students' major advisors—has been well documented in the socialization literature on doctoral education (Barnes and Austin 2009; Noy and Ray 2012; Zhao et al. 2007). Supportive student-advisor relationships can lead to success and retention in doctoral programs, while poor relationships can lead students to leave their doctoral programs altogether (Golde 2000). At the same time, specific modes of interaction have been linked to differential impacts on focal outcomes. For example, Tenenbaum et al. (2001) found that different advisor functions (e.g., instrumental, psychosocial) influence different outcomes. Specifically, they found that while instrumental support predicted levels of scholarly productivity, psychosocial support predicted student satisfaction with their doctoral program. Likewise, Feldon et al. (2016) found that students who engage in research collaborations with department faculty beyond their major advisor were more likely to demonstrate stronger trajectories of research skill development.

In contrast to research on the role of faculty in students' development, peer interactions remain relatively under-researched (Flores-Scott and Nerad 2012; Meschitti 2018). This might be because doctoral training has been viewed predominantly through the lens of one-to-one apprenticeship between a doctoral student and faculty advisor (Maher et al. 2013). However, Flores-Scott and Nerad argue that the role of peers in doctoral students' experiences is different from that of faculty advisers and warrants further investigation. Especially in scientific fields, team-based endeavors are increasingly common (Cumming 2009), resulting in more complex collaboration and mentoring structures for graduate students to the extent that "cascading mentorship" (i.e., postdocs mentoring graduate students, senior students mentoring junior students, etc.) has become a signature pedagogy in many sciences (Golde et al. 2006).

Analyzing Individual Differences in Socialization over Time

While socialization experiences have long been the focus of attention in research on doctoral education, the vast majority of studies have relied on conventional variable-oriented approaches. Variable-oriented analyses tend to emphasize the level of particular features within an environment or collection of individuals, without regard for context or the heterogeneity of individuals within the sample. For example, Weidman and Stein (2003) examined doctoral students' perceptions of a supportive faculty environment as a function of perceived department collegiality, student-faculty interactions, student scholarly engagement, and student-peer interactions without regard for individual differences in students' progress toward degree or the potential lack of independence among perceptions of collegiality, interactions, and encouragement. Because students experience facets of socialization as interconnected within a broader milieu, it would be expected that constellations of relationships amongst these variables might exist, with subsets of participants reflecting specific configurations that would not be detectable within a variable-oriented regression framework. Further, in that framework, identifiable variance contributed by each term represents the unique contribution per variable; as such, researchers often do not unpack the variance accounted for jointly by multiple variables. In contrast, a person-oriented approach empirically tests for these commonalities amongst subsets of participants (Sterba and Bauer 2010; Muthén and Muthén 2000). Using a bottom-up process, person-oriented analyses aggregate up from the level of the individual and facilitate grouping with other, similar individuals who can be classified based on their similarities, rather than making the a priori assumption of generalization across the whole sample (von Eye and Bogat 2006).

Further, doctoral socialization is inherently a longitudinal and dynamic process in which students' experiences and desired support vary greatly depending on their stage of training (Gardner 2010b). The salience of specific types of interactions with others to students' development may change over time, as collegial research interactions and greater scholarly independence may have disproportionate impact as students transition into the later years of their programs of study (Austin 2002; Lovitts 2005; Weidman et al. 2001). Disciplinary norms in the structure of doctoral programs also play a role in the timing of various formative experiences. For example, in biology departments, students typically rotate through multiple laboratories during their first year with the goal of finding a match for a permanent lab placement with a major professor starting in their second year (Maher et al. 2018). Thus, the circumstances of socialization change markedly as students find a "permanent home" for the remainder of their studies. While these factors highlight the importance of longitudinal data, relatively limited research has been done to longitudinally examine doctoral socialization experiences. In addition, within a person-oriented framework, researchers can identify the ways in which patterns within facets of socialization shift over time and across differing phases of the dynamic context of doctoral training at the level of the individual. In sum, person-oriented analyses are advantageous by allowing researchers to categorize dynamic processes and can be used to examine such dynamic processes across time.

Inequity in Socialization Experiences

Inherent to the person-oriented approach is the recognition that not all individuals and demographic groups necessarily experience equitable opportunities to develop within doctoral training structures. While the biological sciences represent the most gender-equitable and ethnically diverse field within STEM (science, technology, engineering, mathematics) disciplines in the United States in terms of Ph.D. attainment (52% female; 32% non-White, with the highest proportion of Black/African American and Latino/Hispanic respondents as a pooled group), inequities persist (National Center for Science and Engineering Statistics 2017; National Science Foundation 2015). For example, despite the fact that women represent over half of Ph.D. recipients in the biological sciences, female postdocs remain underrepresented in the most prestigious laboratories, resulting in only 29%–36% of entering tenure-line faculty at research institutions being female (Sheltzer and Smith 2014). At the same time, while URM students are entering doctoral programs in biology in increasing numbers, they remain vastly underrepresented in the field (Meyers et al. 2018). Further, despite some changing demographics in the biological sciences, women, people of color, and international students often report their experiences in the field to be marginalizing (Twale et al. 2016; Eddy et al. 2014; Nettles 1990; Le and Gardner 2010). The present work contends with these inequities by exploring how sociodemographic characteristics predict patterns of faculty and peer interaction, building on prior studies that have found disparities in socialization experiences among doctoral students with different demographic or cultural backgrounds (Felder et al. 2014; Nettles 1990; Sallee 2011).

Conceptual Framework

This study is guided by existing literature on graduate socialization theory, which provides a framework for understanding the relationships and interactions that shape students' development throughout the doctoral program (Weidman et al. 2001). Doctoral training can be understood as a developmental process of socialization, where students socialize into multiple roles within their academic programs, research groups, and broader academic disciplines. As such, the unique features of each provide essential context for understanding the socialization process (Gardner 2010b). During socialization in a laboratory biology context, faculty and peers are key agents that shape individual doctoral students' daily experiences and influence their desired doctoral outcomes (Cumming 2009). The present work pulls from this existing literature and theory to focus on these key socialization agents. More specifically, using a person-centered approach, we examine *patterns* in faculty and peer interactions to create a more nuanced understanding how of faculty and peer interactions together shape the socialization experience of doctoral students.

According to Weidman et al. (2001), socialization describes the "process of internalizing the expectations, standards, and norms of a given society, which includes learning the relevant skills, knowledge, habits, attitudes, and values of the group that one is joining" (Austin and McDaniels 2006, p. 400) through a process of acculturation into their academic disciplines and university life. As such, doctoral socialization literature has focused on the formal and informal processes and experiences of graduate education through the lens of interpersonal interactions with faculty and other students as they relate to various outcomes: affective measures of identity, sense of belonging, self-efficacy, and scholarly productivity (Curtin et al. 2013; Feldon et al. 2016; Kuo et al. 2017; Overall et al. 2011).

Although socialization is conceptualized as a longitudinal process during which the dominant modes of impact change (i.e., stages of socialization), very few studies have collected data from the same participants over time. To complement the existing literature, the present study identifies patterns in reported peer and faculty interactions across a sample of Ph.D. students in the US over the course of 3 years and connects them to the following outcomes: sense of belonging, satisfaction with academic and intellectual development, commitment to institution, and scholarly productivity. We were particularly interested in how these outcomes changed from year to year as a function of changing interaction patterns with faculty and peers.

Method

Participants

The present study is part of a larger research project that seeks to longitudinally examine the developmental trajectory of doctoral students' socialization experiences and relevant outcomes over 4 years (n = 336). Participants were recruited as they entered their doctoral programs in one of two ways. First, department chairs and program directors of the largest 100 biological sciences Ph.D. programs, public flagship universities and minority serving institutions[1] with Ph.D. programs were contacted by email and were asked to inform incoming Ph.D. students of the research study. Second, recruitment emails were sent to several listservs including the American Society for Cell Biology and the Center for the Integration of Research, Teaching, and Learning Network. Students who responded to these emails were entering their Ph.D. programs in one of the 100 originally contacted universities. Prospective participants were then screened to ensure they understood the expectations for participation and met the appropriate criteria for participation.

In the first year of the larger project, all participants entered Ph.D. programs in laboratory-based biological sciences (e.g., cellular and molecular biology, microbiology, developmental biology) across 53 institutions in the United States, representing 26.1% of the institutions contacted. The majority of the universities (79%) were classified as Carnegie R1 institutions (i.e., highest research activity). Due to study attrition and survey response rate, sample size decreased across each year of data collection, with a Year 4 sample of n = 251. Based on exit interviews with willing participants, at least half of attrited participants withdrew from their Ph.D. programs, which precipitated their removal from the study.

Participants were asked to complete annual surveys regarding their Ph.D. experiences and scholarly productivity. The current analysis used data from the second to fourth years of the large study, because Ph.D. programs in the biological sciences typically do not assign students to permanent supervised research laboratories until the beginning of the

[1] Minority serving institutions include historically Black colleges and universities (HBCUs) and Hispanic-serving institutions (HSIs) for this study.

Table 1 Participant demographic distribution

	N	%	% GSS
Gender			
Female	200	59.5	53.6
Male	132	39.3	46.4
Missing	4	1.2	–
International student status			
Domestic	266	79.2	75.2
International	66	19.6	24.8
Missing	4	1.2	–
First-generation student status			
Non first-generation	235	69.9	–
First-generation	96	28.6	–
Missing	5	1.5	–
URM student status			
White	200	59.5	65.0*
Asian	71	21.1	11.3*
URM	59	17.6	18.8*
Missing	6	1.8	5.0*
Carnegie classification			
R1 institutions (highest research activity)	42	79.2	77.1
R2 institutions (higher research activity)	7	13.2	15.2
Other	4	7.5	7.7

*Race and ethnicity data are only available for US citizens and permanent residents in the nationally representative comparison group. *GSS* Survey of graduate students and postdoctorates in science and engineering

second year (Maher et al. 2018). Table 1 presents the demographic distribution of the sample in comparison to a nationally representative study of Ph.D. students [Survey of Graduate Students and Postdoctorates in Science and Engineering,[2] NSF (2017)].

Measures

Student-Faculty and Student-Peer Interactions

The primary focus of this study was to longitudinally examine doctoral students' interactions with faculty and peers using a person-centered approach. From Weidman and Stein's (2003) survey of doctoral student socialization, we used eight binary items that gauge the occurrence of student interactions with faculty and peers. Students were asked to indicate (yes or no) whether they experienced specific modes of interaction with any faculty

[2] The present study demographics are similar to the reported demographics in Survey of Graduate Students and Postdoctorates in Science and Engineering. The one difference was race/ethnicity because race/ethnicity in the Survey of Graduate Students and Postdoctorates in Science and Engineering was only collected on U.S. citizens and permanent residents.

Table 2 Survey items used in the study

Student-faculty and student peer interactions (dichotomous scale; 1 = yes and 0 = no)
Is there any professor in your department with whom you…
1. Sometimes engage in social conversation
2. Often discuss topics in his/her field
3. Often discuss other topics of intellectual interest
4. Ever talk about personal matters
Is there another student in your department with whom you…
5. Sometimes engage in social conversation
6. Often discuss topics in his/her field
7. Often discuss other topics of intellectual interest
8. Ever talk about personal matters
Sense of belonging (11-point Likert scale; strongly disagree to strongly agree)
1. I feel a sense of belonging to my lab/research group.
2. I feel that I am a member of the lab/research group community.
3. I see myself as part of the lab/research group community.
McDonald's Omega = 0.95 for Year 2, 0.97 for Year 3, 0.96 for Year 4
Academic and intellectual development (3-point Likert scale; disagree to agree)
1. I am satisfied with the extent of my intellectual development since attending this institution.
2. My academic experience has had a positive influence on my intellectual growth and interest in ideas.
3. I am satisfied with my academic experience at this institution.
McDonald's Omega = 0.88 for year 2, 0.86 for year 3, 0.87 for year 4
Institutional commitment (3-point Likert scale; disagree to agree)
1. I am certain this institution is the right choice for me.
2. I am confident I made the right decision in choosing this institution.
3. I feel I belong at this institution.
McDonald's Omega = 0.86 for Year 2, 0.87 for Year 3, 0.87 for Year 4

member or peer in their department. Table 2 presents all eight faculty-peer interaction items.

Predictor Variables

Given that doctoral interactions with faculty and peers may differ as a function of different demographic backgrounds (Roksa et al. 2018), we used four self-reported independent variables—gender, international student status, first-generation student status, and race/ethnicity. For this study, first-generation students refer to those for whom neither parent completed a 4-year college degree. In addition, race/ethnicity was coded into three categories: White, Asian, and URM (i.e., Latino, Black, native Hawaiian/American/Alaskan).

Outcome Variables

Previous studies indicate that students' interactions with peers and faculty during their doctoral training are linked to a variety of student outcomes (Gardner 2007; Nettles and Millett 2006). Our study employed four different outcome measures: sense of belonging, satisfaction with academic and intellectual development, institutional commitment, and scholarly productivity (see Table 2).

Measures of students' sense of belonging indicated the extent to which they felt connected to their laboratory or research group community (3 items; Bollen and Hoyle 1990). Students' perceived satisfaction with academic and intellectual development assessed the extent to which students were satisfied with their academic experience and growth at their institution (3 items; Nora and Cabrera 1996). Institutional commitment measured the extent to which students felt confident in the selection of their institution (3 items; Nora and Cabrera 1996). The mean scores of the three items of each outcome variable were used for analysis. Research productivity measured both the number of first-authored journal articles and the total number of journal articles that participants published during the given academic year. These reported citations were independently confirmed by the research team via bibliographic databases, and unconfirmed citations were not included in analyses. Lastly, student attrition in degree programs tracked the individual students' enrollment status at the end of the given academic year (enrolled = 1; withdrew = 0). The program attrition data from those who voluntarily left the study were not included in analyses.

Statistical Analyses

Latent Class Analyses

To examine if distinct and unique subgroups existed among doctoral biology students with respect to their interactions with faculty and peers, we first performed latent class analyses (LCAs) for each of the 3 years separately. LCA is a type of mixture modeling technique for identifying unobserved subpopulations in a known group based on responses to a set of observed variables (Hagenaars and McCutcheon 2002; Muthén and Muthén 2000; Vermunt and Magidson 2002). LCA offers many advantages over other traditional cluster analysis techniques (e.g., k-means) in that it is a probabilistic and model-based approach (Magidson and Vermunt 2002; Vermunt and Magidson 2002).

In this study, an LCA model estimates two types of model parameters: the probability of answering yes or no to each of the eight faculty-peer interaction questions within each class and the relative prevalence (i.e., proportion) of each class. In order to find an LCA model that fits best to the data, we estimated a series of models with differing numbers of latent classes ranging from one to six. The final model selection was based on several model fit criteria. These criteria included Bayesian Information Criterion (BIC; Schwartz 1978), Vuong-Lo-Mendell-Rubin (VLMR) likelihood ratio test (Vuong 1989), and Entropy (Celeux and Soromenho 1996). The BIC is a descriptive index for comparing models, wherein smaller BIC values are indicative of preferred models. In fact, a recent simulation study (Nylund et al. 2007) showed that the BIC is the best indicator for determining the optimal number of latent classes. The VLMR test provides evidence that a model with k latent classes is significantly better than a model with k-1 latent classes. Entropy assesses models in a post hoc manner by which a model with an entropy value closer to 1 indicates more accurate classification of a group into subpopulations. In addition to these statistical criteria, we also examined practical and theoretical interpretability of the class solution (Collins and Lanza 2010).

Latent Transition Analyses

To explore how doctoral students' interaction group membership changed over time during their doctoral training, we next conducted a latent transition analysis (LTA), which is an extension of LCA to longitudinal data (Collins and Lanza 2010; Nylund-Gibson et al. 2014). LTA uses an autoregressive modeling technique to investigate individuals' transition across latent classes over time. It is used to estimate the probabilities of transitioning from a given latent class at time t to another latent class at time $t+1$. Given that an LCA model is the most commonly used measurement model for an LTA (Nylund 2007), our study employed the prior cross-sectional LCA models as measurement models for our LTA model specifications.

In order to determine the best-fitting LTA model, we estimated four LTA models: a baseline LTA model with no assumptions about the model structure across time, a model with measurement invariance across time, a model assuming transition stationarity, and a model including a second-order effect. These models were examined as recommended by Nylund (2007) for examining LTA. We then compared these models using Likelihood-Ratio Tests (LRT; Bollen 1989) and BIC values. Significant LRT results ($p < 0.05$) indicated that a less parsimonious model was preferred. Once the final LTA model was chosen, the transition probabilities of all latent classes were estimated.

Logistic Regressions Analysis Based on Transition Profile

Because many transition patterns found by the final LTA model contained only one or two individuals, we grouped individuals with substantively similar transitions together. We dubbed these groups *transition profiles* and labeled them descriptively. These profile identifiers were subsequently employed as categorical variables in multinomial logistic regressions to examine the associations between student demographics (e.g., gender, international student status, first-generation student status, URM student status) and transition profile.

Latent Growth and Multi-group Analyses

We further examined whether transition profiles influenced the growth of four socialization outcomes: sense of belonging, academic and intellectual development, institutional commitment, and research productivity (both first authored and total publications). We employed latent growth curve (LGC) models (McArdle and Epstein 1987) combined with multigroup modeling (Muthén and Asparouhov 2002) to examine this research question. LGC models are commonly used to evaluate the change or growth of continuous variables across time. Multigroup models can be used to determine whether parameter estimates differ or remain equal across pre-specified groups. Combined, multigroup LGC models allowed us to examine whether growth in sense of belonging, academic and intellectual development, institutional commitment, and research productivity differed across the five transition profiles. Further, because we centered our analyses on the Year 4 time point (per Grimm 2012), we were able to examine whether the Year 4 outcome score differed across the five transition profiles.

We estimated multigroup LGC models under various conditions, most importantly constraining fixed and random effects of the intercept and slope parameters equal across groups. Such constraints allowed us to examine: (1) whether the Year 4 outcome variables differed across transition profiles (i.e., did the mean of the intercept parameter differ across groups?); (2) whether the growth of the outcome variables differed across transition profiles (i.e., did the mean of the slope parameter differ across groups?); (3) whether transition profiles contained differential individual variability surrounding the Year 4 outcome variables (i.e., did the variance of the intercept differ across groups?); and (4) whether transition profiles contained differential variability surrounding the growth of the outcome variables (i.e., did the variance of the slope differ across groups?).

We compared nested models using Chi square difference testing, corrected for robust maximum likelihood estimation (Satorra and Bentler 2001). Nested models constrained

Table 3 Descriptive statistics for faculty-peer interaction items

	Number of students responding "yes"	
	Interaction with faculty (%)	Interaction with peers (%)
Engage in social conversation (Year 2)	249 (84.4)	284 (96.3)
Engage in social conversation (Year 3)	240 (87.5)	262 (95.6)
Engage in social conversation (Year 4)	217 (86.5)	246 (98.0)
Discuss topics in his/her field (Year 2)	221 (74.9)	267 (90.5)
Discuss topics in his/her field (Year 3)	199 (72.6)	258 (94.2)
Discuss topics in his/her field (Year 4)	175 (69.7)	228 (90.8)
Discuss other topics of intellectual interest (Year 2)	177 (60.0)	260 (88.1)
Discuss other topics of intellectual interest (Year 3)	163 (59.5)	248 (90.5)
Discuss other topics of intellectual interest (Year 4)	162 (64.5)	231 (92.0)
Ever talk about personal matters (Year 2)	123 (41.7)	261 (88.5)
Ever talk about personal matters (Year 3)	120 (43.8)	253 (92.3)
Ever talk about personal matters (Year 4)	135 (53.8)	230 (91.6)

Sample size: n = 295 for Year 2; n = 274 for Year 3; n = 251 for Year 4

fixed and random parameter estimates equal across groups in a sequential manner. If a nested model fit no worse (i.e., model fit comparisons showed no significant differences) than the more complex model, the model constraint was retained in further analyses. If the best-fitting model contained differences in any parameter across the transition profiles, appropriate statistical tests were conducted to determine between which specific groups differences occurred.

We used Poisson regression to examine differences in the number of first-authored publications across groups. In addition, we implemented one-way analysis of variance to examine attrition across groups within each time point.

All above analyses were run using M*plus* 8.1 (Muthén and Muthén 1998–2017). To handle missing data, we adopted a full information maximum likelihood (FIML) approach. To account for the non-normality of the data, models were fit using the robust maximum likelihood (MLR) estimator. Across analyses, the nested structure of the data (i.e., individuals nested within universities) was taken into account by using the M*plus* command: type = complex.

Results

Descriptive Statistics

Table 3 shows the descriptive statistics for the eight survey items regarding student interaction with faculty and peers. Overall, students' interactions with peers occurred more frequently than their interactions with faculty. The most frequently observed type of interaction was social conversation for both student-peer and student-faculty interactions across all three points of measurement. These results were consistent with previous studies

Table 4 Fit statistics for LCA models for each of the three waves

Model	Loglikelihood	Number of free parameters	BIC	VLMR LRT p value	Entropy
Year 2 (n = 295)					
1-class	− 1045.184	8	2135.863	–	–
2-class	− 891.184	17	1879.046	0.0000	0.812
3-class	− 856.008	26	1859.877	0.1571	0.826
4-class	− 836.618	35	1872.279	0.1174	0.903
5-class	− 824.180	44	1898.587	0.4636	0.903
6-class	− 816.560	53	1934.530	0.2806	0.919
Year 3 (n = 274)					
1-class	− 906.646	8	1858.196	–	–
2-class	− 776.918	17	1649.258	0.0000	0.783
3-class	− 746.607	26	1639.156	0.0128	0.802
4-class	− 732.974	35	1662.407	0.0038	0.840
5-class	− 727.288	44	1701.554	0.4001	0.870
6-class	− 721.734	53	1740.964	0.3161	0.920
Year 4 (n = 251)					
1-class	− 833.322	8	1710.848	–	–
2-class	− 713.122	17	1520.176	0.0000	0.782
3-class	− 695.939	26	1535.540	0.0518	0.816
4-class	− 683.944	35	1561.279	0.4161	0.825
5-class	− 674.773	44	1592.667	0.1904	0.859
6-class	− 666.278	53	1625.404	0.1151	0.885

examining doctoral students' socialization experiences (Anderson and Swazey 1998; Weidman and Stein 2003).

Latent Class Analysis: Identification of Types of Student Interactions

To identify patterns of student-faculty and student-peer interactions among doctoral biology students, we first conducted a series of LCAs with the eight interaction items for each wave separately. Table 4 shows the fit indices for the LCA models estimated with 1–6 latent classes. The BIC values were the lowest for the three-class solution for Year 2 and 3, which indicates that the three-class model was deemed most optimal for both waves of the data. However, for Year 4, the two-class model was found to be the most preferred model according to the lowest BIC value while the three-class model was the second most preferred one. In addition, the VLMR tests were not significant for models with more than two classes for both Year 2 and 4, which suggests that the two-class model was favored for these two waves. However, this was not the case for Year 3; the four-class model was most reasonable according to the VLMR tests. Given that the model fit statistics showed conflicting results about the best-fitting LCA model across three waves of the data, we also considered which model would provide more practically clear and theoretically meaningful interpretation (Collins and Lanza 2010). Consequently, we decided to choose the three-class LCA model for all three waves. The relatively higher entropy values for the three-class models (> 0.8) further indicated that the latent classes identified by the three-class

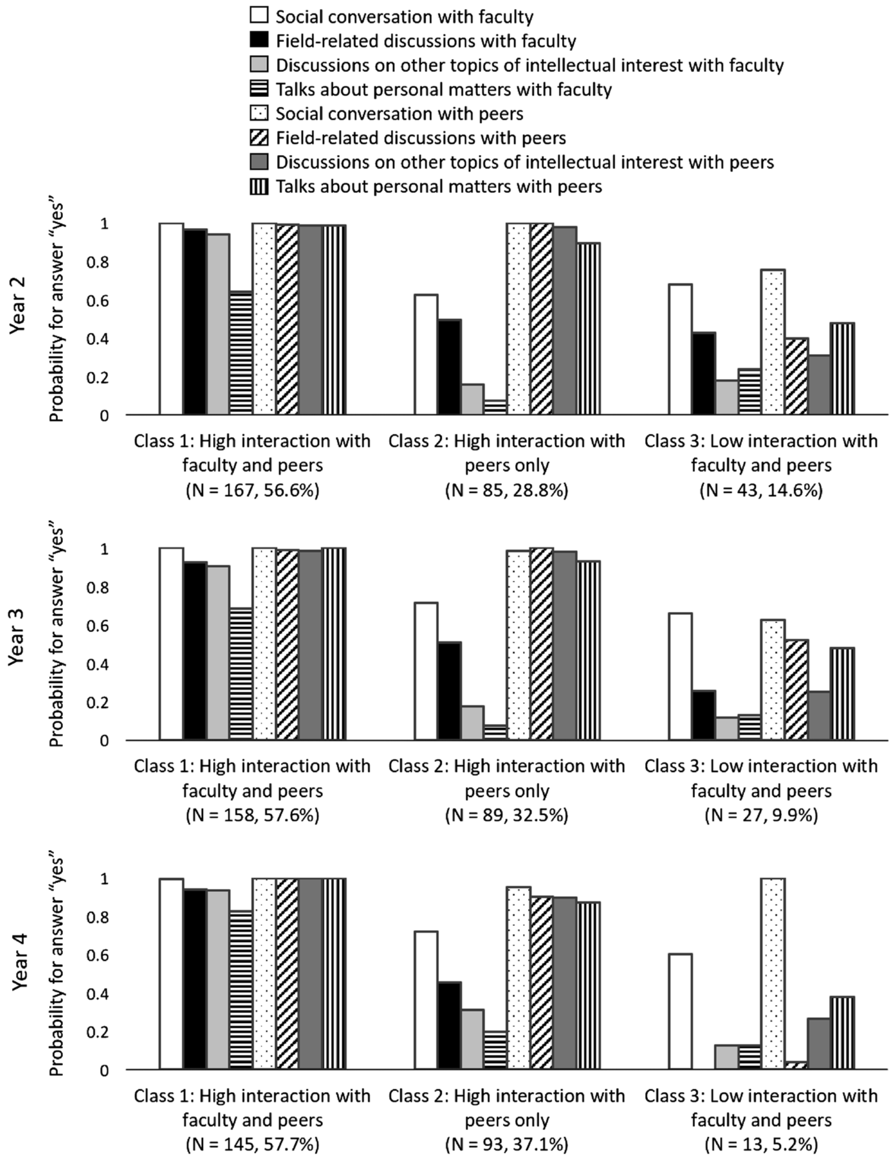

Fig. 1 The interaction profile for the three-class models for Year 2, 3, and 4

models were clearly distinguishable from each other. These results suggest that our sample of doctoral students can be divided into three distinct latent subgroups according to their patterns of faculty-peer interactions in each year (see Fig. 1). These three-class LCA models were also selected as the measurement models to be used in further LTA analyses.

Three different groups of student interactions were identified for our sample (see Fig. 1). Overall, the relative group ordering by size (i.e., the proportion of members in the group) remained consistent over time. The largest number of doctoral students for all three waves was in a group that showed high probabilities for the response "yes" to all of the eight interaction survey items. We therefore labeled this group "high interaction with faculty and peers" (also referred to as latent class 1 [LC1]). The second-largest group showed very high response probabilities of saying "yes" to the four items related to student-peer interactions. This group was labeled "high interaction with peers only" (also referred to as latent class 2 [LC2]). Finally, we labeled the last group "low interaction with faculty and peers" in that results showed comparatively lower probabilities of individuals engaging in six out of eight interaction items (also referred to as latent class 3 [LC3]). Individuals in this group only showed a high probability of engaging in social conversation with peers and faculty. When comparing the group sizes across the three time points, the proportions of the "high interaction with faculty and peers" group are quite similar (56.6% → 57.6% → 57.7%). In contrast, the size of the "high interaction with peers only" group tended to moderately increase over time (28.8% → 32.5% → 37.1%) whereas the "low interaction with faculty and peers" group moderately decreased in size as students advanced through doctoral training (14.6% → 9.9% → 5.2%).

Latent Transition Analysis: Exploring the Transitions Between Interaction Types

Next, we performed LTAs to examine how doctoral biology students' interaction types changed over time. More specifically, our goal was to estimate the probability that students remained in the same interaction group versus transitioning to another interaction group between consecutive time points (i.e., Year 2 to Year 3 and Year 3 to Year 4). We explored four different LTA models: a model with non-measurement invariance (Model 1), a model with full measurement invariance across time (Model 2), a model that assumed stationary transitions across time (Model 3), and a model that examined a second-order effect (Model 4).

We first compared Models 1 and 2 to determine whether the class structure and the item response probabilities differed or remained equal across time. The LRT indicated that Model 1 did not provide a significantly superior model fit than Model 2, $\chi^2 = 41.119$, $df = 48$, $p = 0.74$. This result was also supported by the lower BIC value of Model 2 (BIC = 4625.92) compared to Model 1 (BIC = 4856.05). We therefore concluded that Model 2 was the better-fitting model and assumed measurement invariance in further LTA model specifications.

Next, we tested the assumption of transition stationarity by comparing Model 2 to Model 3. While Model 2 allowed the transition probabilities to be freely estimated across the two transition points, Model 3 constrained the transition probabilities to be equal. The LRT results indicated that the stationarity constraint did not lead to a significant worsening of fit, $\chi^2 = 11.656$, $df = 6$, $p = 0.07$, suggesting that the probabilities of students moving from one class to another from Year 2 to Year 3 were equal to the transition probabilities of students moving from one class to another from Year 3 to Year 4.

Lastly, we tested a model including a higher-order effect. While we only considered first-order effects in Model 2 (i.e., effects of Year 2 on Year 3 and Year 3 on Year 4), we added a second-order effect (i.e., direct effect of Year 2 on Year 4) in Model 4. The LRT indicated Model 4 produced a significant improvement in fit ($\chi^2 = 12.443$, $df = 4$, $p = 0.01$). Although both Model 3 and Model 4 showed a better fit compared to Model 2, we chose Model 3 as our final LTA model based on the lower BIC value of Model 3 (BIC = 4600.15) than that of Model 4 (BIC = 4633.03).

Table 5 Transition patterns based on the final LTA model

Pattern	Number of students (%)						New variable
	Total	Female	INTL	FG	URM	Asian	Transition profile
1→1→1	150 (49.0)	90 (45.0)	11 (21.2)	42 (43.8)	28 (47.5)	18 (25.4)	Stable high interaction—faculty and peers
2→2→2	55 (18.0)	35 (17.5)	13 (19.7)	12 (12.5)	9 (15.3)	12 (16.9)	Stable high interaction—peers
3→3→3	24 (7.8)	11 (5.5)	14 (21.2)	8 (8.3)	4 (6.8)	14 (19.7)	Stable low interaction
2→1→1	12 (3.9)	5 (2.5)	3 (4.5)	2 (2.1)	3 (5.1)	1 (1.4)	Increasing interaction
2→2→1	12 (3.9)	9 (4.5)	2 (3.0)	3 (3.1)	1 (1.7)	3 (4.2)	Increasing interaction
3→2→2	8 (2.6)	6 (3.0)	4 (6.1)	4 (4.2)	2 (3.4)	5 (7.0)	Increasing interaction
3→1→1	6 (2.0)	3 (1.5)	2 (3.0)	1 (1.0)	1 (1.7)	2 (2.8)	Increasing interaction
1→1→2	5 (1.6)	4 (2.0)	1 (1.5)	1 (1.0)	1 (1.7)	2 (2.8)	Decreasing interaction
1→2→2	5 (1.6)	3 (1.5)	1 (1.5)	1 (1.0)	2 (3.4)	1 (1.4)	Decreasing interaction
2→3→2	4 (1.3)	2 (1.0)	4 (6.1)	2 (2.1)	2 (3.4)	1 (1.4)	Unstable
2→3→3	4 (1.3)	3 (1.5)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	Decreasing interaction
3→3→2	4 (1.3)	2 (1.0)	0 (0.0)	0 (0.0)	0 (0.0)	1 (1.4)	Increasing interaction
1→1→3	3 (1.0)	2 (1.0)	2 (3.0)	2 (2.1)	1 (1.7)	2 (2.8)	Decreasing interaction
2→2→3	3 (1.0)	2 (1.0)	1 (1.5)	2 (2.1)	0 (0.0)	2 (2.8)	Decreasing interaction
1→2→1	2 (0.7)	2 (1.0)	0 (0.0)	1 (1.0)	0 (0.0)	0 (0.0)	Increasing interaction
1→2→3	2 (0.7)	0 (0.0)	0 (0.0)	1 (1.0)	0 (0.0)	0 (0.0)	Decreasing interaction
2→1→2	2 (0.7)	2 (1.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	Unstable
3→3→1	2 (0.7)	1 (0.5)	1 (1.5)	0 (0.0)	0 (0.0)	1 (1.4)	Increasing interaction
1→3→1	1 (0.3)	1 (0.5)	0 (0.0)	1 (1.0)	1 (1.7)	0 (0.0)	Unstable
3→1→3	1 (0.3)	1 (0.5)	1 (1.5)	0 (0.0)	0 (0.0)	0 (0.0)	Unstable
3→2→1	1 (0.3)	0 (0.0)	1 (1.5)	1 (1.0)	0 (0.0)	0 (0.0)	Increasing interaction
Total	306 (100)	184 (100)	61 (100)	84 (100)	55 (100)	65 (100)	

ITNL international student status, *FG* first-generation student status

Pattern 1→2→3 indicates that staying in the "high interaction with faculty and peers" (LC1) in Year 2, "high interaction with peers only" (LC2) in Year 3, and "low interaction with faculty and peers" (LC3) in Year 4

Table 6 Transition probabilities based on the final LTA model

		Year 3 (Year 4)		
		LC1	LC2	LC3
Year 2 (Year 3)	LC1	0.911	0.070	0.018
	LC2	0.188	0.718	0.095
	LC3	0.120	0.236	0.644

LC1 = high interaction with faculty and peers; LC2 = high interaction with peers only; LC3 = low interaction with faculty and peers. The transition probabilities between Year 2 and 3 were the same as those between Year 3 and 4

Table 5 details the transition patterns of doctoral students' interaction with their faculty and peers based on the final LTA model. We found 21 patterns occurred out of 27 possible. Overall, the results indicate that students were more likely to remain in the same interaction group from the second to fourth year of doctoral training (n = 229, 74.8%). More specifically, the most common pattern was to remain in the "high interaction with faculty and peers" group (LC1) across three years (n = 150, 49.0%), with the next most common pattern being to stay in the "high interaction with peers only" (LC2) across time (n = 55, 18.0%).

Because many transition patterns contained only one or two individuals, we grouped individuals with substantively similar transitions together. Profiles *Stable High Interaction—Faculty and Peers*, *Stable High Interaction—Peers*, and *Stable Low Interaction* included students who stayed in the "high interaction with faculty and peers" (LC1), "high interaction with peers only" (LC2), and "low interaction with faculty and peers" (LC3) across all years, respectively. In addition, profile *Increasing Interaction* (n = 45) included students who moved from lower to higher interaction groups over time (e.g., 3 → 3→2, 3 → 2→1) while profile *Decreasing Interaction* (n = 22) included those who moved from higher to lower interaction groups (e.g., 2 → 2→3, 1 → 2→3). The remaining students who did not belong to any of the profiles described above were labelled *Unstable Changes* (n = 10; e.g., 2 → 3→2, 1 → 3→1). However, *Unstable Changes* students were excluded from the further analyses, since only 10 (3.3%) were members of this profile and these students' transitions occurred in random or unpredictable ways, making their transitions difficult to interpret.

Based on the final model, the transition probabilities were estimated as shown in Table 6. Since the stationary LTA model turned out to fit our data best, the transition matrix of the first transition point (i.e., Year 2 to Year 3) was the same to that of the second transition point (i.e., Year 3 to Year 4). The transition matrices revealed several interesting patterns. Specifically, students starting in LC1 were most likely to remain in that latent class for the following years; 91.1% of the students in this group stayed in LC1 from Year 2 to Year 3 as well as Year 3 to Year 4. On the other hand, students starting in LC3 were least likely to be members of that latent class in the following year; 64.4% from the first year remained in the same latent class in the following year, while 35.6% moved to other groups. These results also indicate that students were more likely to move from lower to higher levels of interaction over time. However, of the students who were in the "low interaction with faculty and peers" (LC3) group, 23.6% changed their group to the "high interaction with peers only" (LC2) by the next year but only 12.0% moved to the "high interaction with faculty and peers" (LC3). This result may imply that it took time for these students to become actively engaged with both faculty and peers; they would establish peer interactions first and then start to interact with their faculty.

Predictors of Transition Profile in Interactions: Demographic Characteristics

Using transition profiles as categorical variables, we conducted a series of multinomial logistic regression analyses to examine whether doctoral students' likelihood of membership in a given transition profile were influenced by their demographic backgrounds (e.g., gender, international student status, first-generation status, URM status) (see Table 7).

Membership in specific transition profiles were found to be significantly predicted by different demographic factors. Male participants were more likely than female participants to be in the *Stable Low Interaction* profile compared to the *Stable High Interaction—Peers* profile (OR 2.85, 95% CI 1.03, 7.87). This result means that male students were more almost three times as likely as their female counterparts to remain in the latent class characterized by low interaction with both faculty and peers (LC3). Conversely, female students were more likely to remain in the latent class characterized by low interaction with faculty and high interaction with peers (LC2). When compared with domestic doctoral students, international students were more likely to be in *Stable High Interaction—Peers* (OR 3.78, 95% CI 1.73, 8.28), *Stable Low Interaction* (OR 9.15, 95% CI 3.72, 22.51), and *Increasing Interaction* (OR 4.36, 95% CI 1.59, 11.98) rather than being in *Stable High Interaction—Faculty and Peers*. In other words, international students were the least likely to sustain frequent interactions with both faculty and peers across the 3-year period. No significant associations were found between URM status and transition profile. However, Asian doctoral students were more likely than their White peers to remain in the *Stable Low Interaction* profile relative to the *Stable High Interaction—Faculty and Peers* profile (OR 6.78, 95% CI 2.48, 18.54) and *Stable High Interaction—Peers* (OR 5.54, 95% CI 1.76, 17.50). These students were also more likely than their White peers to be in the *Decreasing Interaction* rather than *Increasing Interaction* profile (OR 4.05, 95% CI 1.19, 13.80). These results show that Asian students were more likely to have low levels of interaction with both faculty and peers across their 3 years of doctoral training or they tended to move from initially higher levels to lower levels of interaction.

Relations Between Transition Profile and Socialization Outcomes

Four socialization outcomes were examined in relation to transition profile membership: sense of belonging, perception of academic and intellectual development, institutional commitment, and scholarly productivity. The relationship among transition profile and socialization outcomes were examined using multigroup latent growth curve models centered at Year 4, the final timepoint. The grouping variable was transition profile. This analysis allowed us to determine whether transition profile influenced (1) the change in socialization outcomes across time, (2) the value of the socialization outcome at Year 4, and (3) the relationship between change and the value at Year 4.

For each socialization outcome, we first fit a multigroup intercept-only latent growth curve (LGC) model (Model 1). Next, we fit a multigroup linear effects LGC model (Model 2). Both of these models assumed strong invariance. We further examined strict invariance across groups (Model 3). Next, we fit models constraining fixed effects equal across profiles to examine whether the value of socialization at Year 4 as well as the change in socialization from Year 2 to Year 4 remained equal across transition profiles (Models 4 and

Table 7 Associations of demographic characteristics and interaction transition profiles

	Odds Ratios (95% Confidence interval for odds ratio results)				
	Male vs. Female	INTL vs. Domestic	First-gen vs. non-first-gen	URM vs. White	Asian vs. White
Stable high interaction—peers vs. stable high interaction—faculty and peers	0.9 (0.4, 1.8)	3.8 (1.7, 8.4)*	0.7 (0.3, 1.5)	0.9 (0.3, 2.5)	1.2 (0.4, 3.4)
Stable low interaction vs. stable high interaction—faculty and peers	2.6 (0.9, 6.8)	9.2 (3.7, 22.5)*	0.9 (0.3, 2.7)	2.2 (0.4, 11.1)	6.8 (2.5, 18.5)*
Increasing interaction vs. stable high interaction—faculty and peers	1.2 (0.6, 2.6)	4.4 (1.6, 12.0)*	0.8 (0.3, 1.7)	0.8 (0.3, 2.1)	1.7 (0.8, 3.7)
Decreasing interaction vs. stable high interaction—faculty and peers	1.0 (0.4, 2.4)	2.7 (0.7, 9.9)	1.1 (0.4, 3.0)	1.1 (0.3, 3.5)	1.9 (0.6, 5.8)
Stable low interaction vs. stable high interaction—peers	2.8 (1.0, 7.9)*	2.4 (0.9, 6.4)	1.3 (0.4, 4.3)	2.4 (0.6, 9.1)	5.5 (1.8, 17.5)*
Increasing interaction vs. stable high interaction—peers	1.3 (0.5, 3.4)	1.2 (0.5, 2.8)	1.1 (0.4, 3.0)	0.8 (0.3, 2.4)	1.4 (0.4, 4.9)
Decreasing interaction vs. Stable high interaction—peers	1.1 (0.3, 3.8)	0.7 (0.2, 2.9)	1.6 (0.6, 4.7)	1.2 (0.3, 3.9)	1.6 (0.3, 8.0)
Decreasing interaction vs. stable low interaction	0.4 (0.1, 1.3)	0.3 (0.1, 1.2)	1.2 (0.4, 3.5)	0.5 (0.1, 2.7)	0.3 (0.1, 1.1)
Decreasing interaction vs. increasing interaction	2.1 (0.9, 5.3)	2.1 (0.8, 5.4)	1.2 (0.4, 3.8)	2.8 (0.6, 13.5)	4.1 (1.2, 13.8)*
Stable low interaction vs. increasing interaction	0.8 (0.2, 2.6)	0.6 (0.2, 1.9)	1.4 (0.6, 3.6)	1.4 (0.4, 4.8)	1.1 (0.4, 3.5)

When X vs. Y, Y was the reference group

*$p < 0.05$

Table 8 Model fit statistics for LGC models

Model	χ^2	*df*	Δ_{χ^2}	*p*	CFI	BIC
Sense of belonging						
1. Intercept only LGC	44.78	20	–	–	0.78	3241
2. Linear effects LGC	5.98	5	38.47	.00*	0.99	3289
3. Strict invariance	76.65	17	67.24	.00*	0.47	3298
4. Fixed effects intercept equality	20.49	9	16.73	.00*	0.90	3277
5. Fixed effects slope equality	11.29	9	5.34	.25	0.98	3271
6. Random effects intercept equality	30.86	13	18.69	.00*	0.84	3266
7. Random effects slope equality	27.91	13	13.67	.01*	0.87	3267
7a. Set negative non-significant variances to 0	22.62	14	10.11	.07	0.92	3256
8. Equal correlation between slope and intercept	25.41	16	2.85	.24	0.92	3248
Academic and intellectual development						
1. Intercept only LGC	16.52	20	–	–	1.00	957
2. Linear effects LGC	5.53	5	11.47	.72	1.00	1026
3. Strict invariance	32.41	32	14.52	.27	1.00	920
4. Fixed effects intercept equality	43.13	36	23.89	.00*	0.93	909
6. Random effects intercept equality	63.38	36	39.05	.00*	0.74	944
Institutional commitment						
1. Intercept only LGC	36.80	20	–	–	.90	1057
2. Linear effects LGC	12.89	5	24.02	.06	.96	970
3. Strict invariance	54.07	32	18.37	.10	.87	1019
4. Fixed effects intercept equality	60.75	36	6.63	.16	.86	1001
6. Random effects intercept equality	65.87	40	5.08	.28	.85	985
Number of journal articles						
1. Intercept only LGC	43.28	20	–	–	0.50	1873
2. Linear effects LGC	6.87	5	35.66	.00*	0.96	1920
3. Strict invariance	24.85	17	17.78	.12	0.83	1880
4. Fixed effects intercept equality	27.10	21	1.42	.84	0.87	1859
5. Fixed effects slope equality	32.67	25	5.69	.22	0.84	1842
6. Random effects intercept equality	36.17	19	3.65	.72	0.85	1824
7. Random effects slope equality	39.34	33	4.66	.99	0.86	1808
8. Equal correlation between slope and intercept	65.68	37	53.17	.00*	0.39	1815

Δ_{χ^2} = change in Chi square. [a]Because models used MLR estimation, we included appropriate correction factors when computing all Chi square difference values and conducting Chi square difference tests

*$p < .05$

5, respectively). Fourth, we fit models constraining random effects equal across groups to examine whether the variance of socialization at Year 4 as well as the variance of change from Year 2 to Year 4 remained equal across profiles (Models 6 and 7, respectively). Finally, we examined the relationship between growth and final scores across profiles (Model 8) to examine whether transition profile impacted the relationship between Year 4 socialization outcome scores and change across time.

Table 8 reports model fit statistics for LGC models. Overall, it was found that fixed and random effects of Year 4 sense of belonging scores differed across profiles, as shown by the significant differences between sense of belonging Models 3 and 4, $\Delta_{\chi^2} = 16.73$, $df = 4$, $p = .002$, and Models 5 and 6, $\Delta_{\chi^2} = 18.69$, $df = 4$, $p = .001$. Specifically, overall sense of belonging at Year 4 was greater for the *Stable High Interaction—Faculty and Peers* profile ($M = 9.15$) than for *Stable High Interaction—Peers* ($M = 8.51$), $p = .002$. Greater individual variability in sense of belonging was found in the *Stable Low Interaction* profile ($s^2 = 4.92$) than either the *Stable High Interaction—Faculty and Peers* ($s^2 = 1.57$) or *Stable High Interaction—Peers* ($s^2 = 1.36$) profiles. Further, it was found that random effects of the change in sense of belonging differed across profiles, as shown by the significant difference between Models 6 and 7, $\Delta_{\chi^2} = 13.67$, $df = 4$, $p = .01$. *Stable High Interaction—Faculty and Peers* and *Stable High Interaction—Peers* were found to have zero individual variability in the change trajectory. However, significant individual variability in the change trajectory was found for both *Increasing Interaction* ($s^2 = 1.07$) and *Decreasing Interaction* ($s^2 = 4.00$), indicating that sense of belonging changes in a non-uniform fashion across individuals within these two profiles. A closer examination of individual values showed both positive and negative growth within the *Increasing Interaction* and *Decreasing Interaction* profiles.

The best fitting model for institutional commitment constrained fixed and random effects equal across groups. Thus, no differences across profiles could be examined for institutional commitment. It was concluded that no differences existed across any groups due to this finding.

For academic and intellectual development, it was found that fixed and random effects of the Year 4 scores differed across profiles, shown by the significant difference between Models 3 and 4, $\Delta_{\chi^2} = 23.89$, $df = 4$, $p < .001$, and Models 3 and 6, $\Delta_{\chi^2} = 39.05$, $df = 4$, $p < .001$. Specifically, the *Stable High Interaction—Faculty and Peers* profile ($s^2 = 0.05$) had lower variance surrounding the mean value of academic and intellectual development at Y4 than *Stable High Interaction—Peers* ($s^2 = 0.27$), *Stable Low Interaction* ($s^2 = 0.40$), and *Increasing Interaction* ($s^2 = 0.14$). Additionally, *Increasing Interaction* had significantly lower variance than *Stable Low Interaction*.

The best fitting model for institutional commitment constrained fixed and random effects equal across groups. Thus, no differences across profiles could be examined for institutional commitment. It was concluded that no differences existed across any groups due to this finding.

For scholarly productivity, the correlation between the Y4 score and change trajectory differed across profiles, shown by the significant difference between research productivity Models 7 and 8, $\Delta_{\chi^2} = 53.17$, $df = 4$, $p < .001$. Doctoral students who published many papers during Year 4 had greater change in the number of articles published from Year 2 to Year 4 in the *Stable High Interaction—Peers* (cor = 1.0) and *Stable Low Interaction* (cor = .94) profiles than students in the *Stable High Interaction—Faculty and Peers* profile (cor = .53). This result may indicate an effect where students with many publications early in their doctoral training cannot feasibly continue to publish increasingly more articles, thus resulting in non-meaningful negative change or no change. It should be noted that Year 2 scores did not have the same relationship with change trajectory, so the number of articles published early in doctoral training did not predict growth in research productivity.

Additionally, for research productivity, we examined whether the number of first-authored publications differed across profiles by examining Poisson regression models. We examined whether the rate of first-authored publications differed across transition profiles. The total number of first-authored publications regardless of year published did not differ across profiles ($.09 \le p \le .98$). When examining differences in first-authored publications at Year 2, *Stable Low Interaction* differed significantly from all other groups, due to no

Table 9 Student attrition within transition profile across years

Transition profile	Year 2	Year 3	Year 4
Stable high interaction—faculty and peers, n = 150 (%)	3 (2)	10 (7)	15 (10)
Stable high interaction—peers, n = 55 (%)	4 (7)	7 (13)	7 (13)
Stable low interaction, n = 24 (%)	0 (0)	3 (13)	4 (17)
Increasing interaction, n = 45 (%)	0 (0)	1 (2)	2 (4)
Decreasing interaction, n = 22 (%)	0 (0)	0 (0)	1 (5)
p-value	0.09	0.13	0.41

N (%). An additional 29 participants were not placed in transition profiles due to attrition

doctoral students in the *Stable Low Interaction* profile reporting a first-authored publication in Year 2. At Year 3, significant differences were found between *Stable High Interaction—Faculty and Peers* and *Stable High Interaction—Peers* ($p = .01$), as well as between *Decreasing Interaction* and *Stable High Interaction—Peers* ($p = .02$). Incidence rate ratios (IRRs) showed that students in *Stable High Interaction—Faculty and Peers* were expected to have a rate of first-authored publications 12 times greater compared to *Stable High Interaction—Peers* (IRR 95% CI 1.73, 95.68). Students in *Decreasing Interaction* were expected to have a rate of first-authored publications 8 times greater compared to *Stable High Interaction—Peers* (IRR 95% CI 1.48, 47.40). At Year 4, no significant differences in rate of first-authored publications were found between groups.

We lastly examined whether student attrition differed across the transition profiles. Overall, 58 doctoral students left their doctoral programs by the end of their fourth year of doctoral study. Table 9 shows the number of participants within each transition profile who left their program by Year 2, 3, and 4. Cross-tabulation results indicated no attrition differences across transition profiles for Year 2 ($p = .09$), Year 3 ($p = .13$) or Year 4 ($p = .41$).

Discussion

In this study, we identify three distinct latent classes that best capture patterns of socialization interactions between students in our sample, their peers, and program faculty: high interaction with both faculty and peers, high interaction with peers only, and low interaction with both faculty and peers. The "high interaction with faculty and peers" group constituted the greatest proportion of the whole sample in each year, followed by "high interaction with peers only," and finally "low interaction with faculty and peers." Given that no studies to date have applied a person-centered approach to the analysis of doctoral students' interactions with faculty and peers, our results may shed new light on group heterogeneity in doctoral socialization. In addition, previous studies have typically investigated student-faculty interaction and student-peer interaction separately. However, our findings highlight that considering faculty and peer interactions simultaneously can provide a more complete picture of how doctoral students are socialized.

Our study further shows that such patterns of doctoral students' interactions with faculty and peers tend to be stable over time in general, with most students staying within their initial latent classes over three years. In addition, students were equally likely to move from one latent class to another during the first transition period (i.e., Year 2 to Year 3) as during the second (i.e., Year 3 to Year 4). Specifically, the "high interaction with faculty and peers" group was the most stable; about 90% of the students in the latent class remained in that class from year to year. This result indicates that once students establish frequent interactions with their faculty members and peers, it may not be difficult for them to sustain such relationships over time. On the other hand, about 64% students in the "low interaction with faculty and peers" remained in that group in the following year, suggesting that without targeted intervention low levels of socialization interaction are unlikely to change. Interestingly, while 24% of the students in this group moved to the "high interaction with peers only" group by the next year, only 12% moved to the "high interaction with faculty and peers" group. This result suggests that, without intervention, peer interactions are more likely to develop over time than interactions with faculty.

Patterns in faculty and peer interactions differed by international student status, race, and gender (but not be first-generation status). International students who did remain stable in their patterns of interaction tended to report low interactions with both faculty and peers across years. These findings are consistent with prior literature documenting that Asian international students reported greater feelings of isolation from faculty compared to students from other groups (Le and Gardner 2010). While researchers have found that international students report a great amount of success in graduate school (Sowell et al. 2008; Roksa et al. 2018) despite inequitable socialization experiences, other research reveals that international students prefer faculty mentors who are "interpersonally involved" in their lives, (Rose 2005, p. 74), suggesting that lower rates of interaction for international students are due to factors beyond student preference.

While the differences by race and gender were less consistent than the findings by international student status, some significant patterns emerged. Relative to white students, Asian students more frequently reported consistently low levels of interactions or low early interaction patterns with higher levels of interacting with faculty and peers in over time. This finding may be due to the fact that 58% of Asian participants in our sample are international. Although our sample size prevented us from doing so in this study, future research might take this into account by examining racial/ethnic differences in an intersectional framework, jointly accounting for both students' citizenship and other demographic characteristics.

Modest gender differences also emerged with men more frequently maintaining lower levels of socialization interaction throughout their program. This is consistent with prior research on ways in which women tend to actively seek out faculty mentors to meet both intellectual and interpersonal needs (Noy and Ray 2012). Future research will also need to examine how characteristics intersectional with gender might further refine and differentiate more nuanced patterns.

Examination of the relationships between transition profiles and socialization outcomes offers more surprising insights. It was expected that students with high levels of interaction with both faculty and peers would be more likely to report a stronger sense of belonging within their research communities than students reporting high levels of interaction only with peers. However, the transition profiles characterized by unidirectional changes in interaction level (i.e., *Increasing Interaction* and *Decreasing Interaction*) did not correspond reliably to concomitant changes in sense of belonging. Whereas participants in the *Increasing Interaction* profile increased their levels of interaction with faculty and/or peers, some members of that transition profile reported increases in their sense of belonging while others reported decreases. Similarly, *Decreasing Interaction* participants decreased their levels of interaction, but did not have uniform directions of change in sense of belonging. This suggests that sense of belonging may be influenced more by stability within an interaction profile over time or other factors that influence that stability than by the frequency or types of interaction themselves. In short, sense of belonging is not a "quick fix," where that outcome is directly enhanced by increases in the types of interaction identified by socialization theory as valuable.

Further, neither levels of academic and intellectual development nor institutional commitment differed significantly as a function of transition profile. While variance in academic and intellectual development did differ across most profiles, the least within-profile variance was associated with two very different profiles: *Stable High Interaction—Faculty and Peers* and *Increasing Interaction*. Much as with expectations regarding sense of belonging, the predictions of socialization theory would suggest that students would both experience greater academic and intellectual development and feel more committed to their academic pursuits if they engaged in higher levels of interaction with faculty and peers. However, this was not observed.

Analysis of publication outcomes as a function of faculty and peer interaction profiles presented different challenges for interpretation. Authorship in general was more likely amongst high interaction classes early in the doctoral process (i.e., Year 2), but it did not differentially predict subsequent growth in publication rate. This suggests that the Matthew effect (i.e., early publications leading to expanding opportunities; Gopaul 2011; Green and Bauer 1995; Merton 1968; Paglis et al. 2006) was not in evidence, as Year 4 publication counts did not differ significantly between profiles. Similarly, the number of first-authored publications did not differ between profiles in that year either, indicating that level of faculty and peer interaction did not predict gains in the level of autonomy or assumption of a leadership role in the production of publications. In Year 3, likelihood of having a first-authored publication was substantially higher for participants in the *Stable High Interaction—Faculty and Peers* profile, but the other transition profile with higher first-authorship rates than other profiles was *Decreasing Interaction*, suggesting inconsistent relationships between socialization profile and scholarly productivity. Thus, it seems that high levels of faculty and peer interaction predict early publication success, but that the importance of high levels of interaction may wane over time.

Limitations

There are several limitations in our study. First, the instruments used in this study relied on yes–no questions as a means of measuring faculty and peer interactions; students were not asked to answer how many faculty and peers they interacted with in those ways or how often. Thus, these items may not accurately reflect the total amount of interaction with faculty and peers for each student. These items were also limited in capturing the quality of interaction (Roksa et al. 2018). Similarly, the present study focuses exclusively on faculty and peer interactions. While faculty and peers have been identified as the two primary socialization agents in doctoral training, recent research suggests that, within the context of lab sciences, postdocs and other research staff may also play a significant role in shaping doctoral student outcomes (Feldon et al. 2019) and play an increasing role in providing academic labor (Cantwell and Taylor 2015). Therefore, future research should not only employ more nuanced measures of peer and faculty interactions but should also consider other socialization agents such as postdocs and research staff, accounting for changing academic labor practices in laboratory-based sciences.

Second, we restricted our sample to laboratory biological sciences, which may make it difficult to generalize our findings to other disciplines. In fact, previous studies have shown that doctoral socialization experiences are substantially different depending on departmental and disciplinary culture and norms (Gardner 2010a) and that doctoral training in laboratory-based sciences is distinct from that of other fields (Cumming 2009).

Third, the sample size was relatively small given the complexity of the analyses presented. Sample size constraints also made it necessary to aggregate racial/ethnic groups into white, Asian, and URM categories. Thus, the analyses may not capture racial/ethnic differences between groups. Similarly, sex was asked in a binary way (i.e., female/male); as such, our findings are not generalizable to non-binary students. Further, the sample contained individuals nested within universities, which could have affected the power to detect small effects. Future research could examine samples with more individuals, more universities, and more nuanced demographic variables to examine the extent to which the findings would be replicated.

Finally, our methodological approach does not allow us to make causal inferences regarding socialization theory. While our findings still provide valuable insights that challenge traditional notions of socialization, we cannot definitively conclude whether or not patterns of interactions cause key doctoral student outcomes.

Implications

Socialization theory as articulated by Weidman et al. (2001), Twale et al. (2016), and others (Gardner and Mendoza 2012) specifies a set of functions and constructs (i.e., mechanisms; Rojas 2017) that interact to shape the development and subsequent outcomes of graduate students. This nexus of process and product suggests that understanding the socialization experiences of doctoral students should permit reasonably accurate predictions about outcomes of interest during their graduate training. Despite this widely held supposition, there have been very few longitudinal studies linking socialization experiences to outcomes to date. Further, most of these have been exclusively qualitative in nature (Holley 2018; Wulff et al. 2004). In the longitudinal work presented here, we statistically examined the following outcomes: attrition, commitment to pursuing the Ph.D. at students' current institution, sense of belonging, scholarly productivity, and students' satisfaction with academic and intellectual development.

In past studies, the support for the predictions of socialization theory have been mixed. For example, Paglis et al. (2006) administered surveys to 130 participants three times over 5.5 years, with a focus on mentorship experiences as predictors of subsequent scholarly productivity, self-efficacy, and commitment to a research career. While the strength of mentoring (operationalized in part as facets of interaction also measured in this study: personal, social, and academic/intellectual) positively predicted productivity and self-efficacy, it did not predict research career commitment. This is noteworthy, because the development of values and identity consistent with the culture of the academic discipline is a central emphasis of the mechanisms of socialization, among which mentoring figures prominently as a mode of student-faculty interaction (Austin and McDaniels 2006; Weidman et al. 2001). In another study examining the socialization experiences of graduate students in STEM disciplines, Feldon et al. (2016) report that the widening research skills gap between two groups of students over time could not be explained by access to mentorship, opportunities to collaborate on publications, or other socialization factors typically associated with faculty or academic departments.

Similarly, other analyses from the larger study that generated the data reported here identified unexpected trends in the relationships between socialization factors and outcomes. For instance, when comparing the experiences and outcomes of domestic Asian students, domestic White students, and international Asian students, Roksa etal. (2018) found that, after the first 2 years of doctoral study, rates of scholarly productivity did not parallel reported levels of socialization experiences. Specifically, domestic Asian students reported access to and participation in scholarly activities and interactions with faculty and peers at the same levels as their domestic White peers, with international Asian students reporting significantly less. However, the scholarly productivity of international Asian students was on par with that of domestic White students, with both groups publishing significantly more than domestic Asian students. Thus, contrary to the predictions of socialization theory and the findings of Paglis et al. (2006), favorable socialization did not predict stronger outcomes.

The current study finds inconsistent and limited relationships between patterns in interactions considered to be vital to positive socialization and doctoral student outcomes, which indicates substantial limitations in socialization theory's ability to account for influences on the targeted dependent variables. In this context, such evidence collectively raises questions about the ability of the mechanisms specified by socialization theory to predict outcomes.

As the socialization framework continues to evolve, some of these mechanisms may become better understood. For example, Twale et al. (2016) increase the importance of considering the demographic backgrounds of graduate students, which align with our current findings that members of different demographic groups are disproportionately likely to be members of different socialization profiles. These differences highlight the need for researchers and practitioners to contend with inequities in socialization experiences, determining both their causes and strategies for mitigating them. This is especially important to the extent that such inequities may have implications for sustained professional stratification after graduate school.

Research on doctoral socialization should also take into account larger structural influences that shape doctoral training experiences, particularly in light of changing research expectations and labor practices in laboratory-based sciences. Due to increased demands on faculty members' time and expectations for research productivity, student-advisor relationships in lab science contexts, especially in the biological sciences, may be rife with exploitation when advisors view graduate students as cheap labor (Zhao et al. 2007). Further, Noy and Ray (2012) posit that, in laboratory settings, "advisors are both mentors and bosses…and advisors may provide less affective and instrumental support due to the structural conditions of the lab and culture of the discipline." (p. 881). Given that the present study provides little empirical support for the traditional claims of socialization theory, we posit that attention to academic labor practices (including the possible exploitation of graduate student labor) and other structural and programmatic influences may be key to understanding differential student outcomes, which appear to be shaped by more than faculty and peer interactions alone.

Further research is warranted to either detect more nuanced influences in postulated socialization mechanisms or identify alternative mechanisms that might better account for changes in these outcomes. However, it must be kept in mind that we do not yet know how these differential socialization experiences might shape outcomes in the future. Even if patterns of interaction do not have a significant impact on doctoral students' development during their Ph.D. programs, those students with have higher levels of interaction with faculty and peers might be better able to build larger networks that will advantage them on the job market and in future career endeavors.

Acknowledgements The authors gratefully acknowledge the support of the National Science Foundation. This material is based upon work supported under Awards 1431234 and 1760894. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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