Received: 27 August 2022 | Accepted: 22 October 2022

DOI: 10.1002/jad.12118

RESEARCH ARTICLE

Foundation for PSA WILEY

Apt and actionable possible identities matter: The case of academic outcomes

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Funding information

Department of Education, Institute for Education Science; Department of Education, Investing in Innovation

Abstract

Introduction: We review the longitudinal evidence documenting that middle and high school students with school-focused possible future identities subsequently attain better school outcomes. Consistent results across operationalizations of possible identities and academic outcomes imply that results are robust. However, variability in study designs means that the existing literature cannot explain the process from possible identity to academic outcomes. We draw on identity-based motivation theory to address this gap. We predict that imagining a possible school-focused future drives school engagement to the extent that students repeatedly experience their school-focused future identities as apt (relevant) and actionable (linked to strategies they can use now).

Methods: We operationalize aptness as having pairs of positive and negative school-focused possible identities (balance) and actionability as having a roadmap of concrete, linked strategies for school-focused possible selves (plausibility). We use machine learning to capture features of possible identities that predict academic outcomes and network analyses to examine these features (training sample USA 47% female, $M_{age} = 14$, $N_1 = 602$, $N_2 = 540$. Test sample USA 55% female, $M_{age} = 13$, $N = 247$).

Results: We report regression analyses showing that balance, plausibility, and our machine algorithm predict better end-of-school-year grades (grade point average). We use network analysis to show that our machine algorithm is associated with structural features of possible identities and balance and plausibility scores.

Conclusions: Our results support the inference that student academic outcomes are improved when students experience their school-focused possible identities as apt and actionable.

KEYWORDS

academic expectations, academic outcomes, identity-based motivation, machine learning, natural language processing, possible selves

1 | INTRODUCTION

Engaging with school implies something about students' temporally future selves and an array of possibly linking current actions—focusing while in class, playing sports, gossiping with friends, or trying to fit in. Students engage with school at least in part because doing so feels relevant to the person they expect to become and want to avoid becoming. These possible identities can include positive expectations—the "A" student, the athletic student, the popular student, as well as fears—the failing student, the one cut from the team, the one with no friends (Oyserman et al., 2012). To explain how possible identities matter, researchers have considered

We presented early attempts at these analyses in a Society for Experimental Social Psychology talk and a much earlier version as a chapter in O'Donnell's dissertation.

possible identity content, valence, and structure (e.g., for reviews, Horowitz et al., 2020; Hoyle & Sherrill, 2006; Oyserman & Horowitz, in press; Oyserman & James, 2011). We build on this prior work, which uses identity-based motivation (IBM) theory, a social psychological theory of self-regulation, motivation, and goal-pursuit (Oyserman & Horowitz, in press; Oyserman, 2007). IBM draws on the social psychological knowledge base to infer that possible identities reside in associative knowledge networks (e.g., Amodio, 2019; Bodenhausen et al., 2003; Collins & Loftus, 1975) and come to mind more easily if recently or frequently accessed (Bargh & Chartrand, 2014; Loersch & Keith Payne, 2016).

As we detail next, the empirical literature documents significant average effects of school-focused possible identities on academic outcomes during adolescence (middle and high school). We highlight gaps in understanding the causal process by examining the evidence from the experimental literature and the longitudinal literature on possible selves and school outcomes during adolescence. We begin to address these gaps by synthesizing IBM theory (Oyserman, 2007) with network and cognitive approaches. We use machine learning and network analyses to test our prediction that aptness and actionability matter.

1.1 | Theoretical synthesis

1.1.1 | Integrating IBM with cognitive and network approaches

IBM theory starts with the observation that people experience their identities as stable anchors for making predictions regarding what to do and how to interpret experiences (Oyserman, 2007). However, this experienced stability belies identity's context sensitivity (Oyserman, 2019). That is, whether an identity comes to mind and its consequences for behavior are probabilistic. Each depends on the inferences people draw from how easy or difficult thinking about the identity and taking action feels in the moment (Oyserman & Horowitz, in press). This idea is congruent with cognitive and network perspectives, which also predict that the likelihood that something comes to mind depends on how recently and how frequently it has come to mind (Bamakan et al., 2019; Granovetter, 1973; Wasserman & Faust, 1994).

Our synthesis implies that whether a particular aspect of identity comes to mind depends on how recently and frequently it has come to mind. As detailed next, we infer two candidate self-knowledge structures from social network analysis (e.g., Granovetter, 1973) and its applications (e.g., Benedek et al., 2017; Paluck & Shepherd, 2012). Self-knowledge structures can be akin to wheels with hubs and spokes or to disparate clique-like constructions with some bridges across cliques (e.g., Kang et al., 2012; Kitsak et al., 2010). The literature on self-structure in memory suggests that cliques are more likely than wheels for self-knowledge (Kihlstrom & Klein, 1994; Oyserman et al., 2012). Hence, we infer that particular possible identities are more likely to come to mind and influence action if they are bridges that link disparate clique-like self-knowledge networks.

1.1.2 | From possible identities to action

As detailed next, we apply our model to review the empirical literature on the effect of school-focused possible identities on academic outcomes. We predict that these identities are more likely to yield school-focused behavior if students experience them as apt and actionable. We operationalize apt identities as the identities people find more relevant to the situation than other on-the-mind identities and actionable identities as identities people easily translate to action in context.

Our literature review suggests two triggering mechanisms, one content-based and the other more structural. The content-based mechanism is called "balance" (e.g., Oyserman & Markus, 1990) and the structural one is called plausibility (e.g., Oyserman et al., 2004). School-focused balance describes valenced pairs of positive (to-be-attained) and negative (to-be-avoided) school-focused possible identities. Balance may increase the likelihood that a school-focused possible identity feels apt across contexts because when a positive aspect of this identity comes to mind, so does a negative one. Some part of the possible identity, either the positive or the negative, will feel relevant whether the context affords the possibility of working toward (becoming more like a positive) or away from (avoiding becoming like a negative) (e.g., Oyserman et al., 2015). Plausibility describes clusters of possible identities in a content domain linked to concrete strategies, including strategies for addressing social contextual barriers. Higher plausibility scores imply that possible identities and context-relevant strategies for action are likely to be co-activated, increasing the likelihood that a possible identity feels apt and actionable (e.g., Oyserman et al., 2004).

1.2 | Empirical evidence

1.2.1 | Lab-based studies testing causal process

Horowitz et al. (2020) conducted a full systematic review of the experimental literature testing the consequences of school-focused possible identities on school behavior. As they report, to test the causal process, researchers systematically varied how they asked participants to think about their future selves. They randomly assigned participants to consider either their positive or negative valenced future selves (Oyserman et al., 2015; Ruvolo & Markus, 1992) or to consider their future selves as more or less apt (Destin & Oyserman, 2010; Study 2; Landau et al., 2014; Nurra & Oyserman, 2018) or more or less actionable (e.g., Oettingen et al., 2005). For example, Nurra and Oyserman randomly assigned middle and high school students to imagine their future selves as something they would become in the near or the far future. Across experiments, researchers report significant effects on academic outcomes (e.g., turning in an assignment or persistence or engagement with a school task). We infer that valence, aptness, or actionability could each affect immediately subsequent school behavior. At the same time, the experimental literature has two limitations. First, experiments cannot predict how long effects last and whether these mechanisms or something else matters for academic outcomes that accrue over time (grade-point average, years of schooling, and graduation). Second, the currently available lab-based experiments test a single mechanism and cannot shed light on how mechanisms might relate. We turn to the field-based literature to address these issues.

1.2.2 | Field-based studies

We did not find a systematic review of field-based longitudinal studies of the effect of school-focused possible identities on educational attainment and academic outcomes (grades or test scores, completing high school, or going to and completing college), so we created a complete set of field studies using PsychINFO. Our keywords were academic outcome(s), grades, academic attainment AND possible self(ves), future selves, possible identities, aspirations, and expectations. We followed up this search by looking at the reference list of selected papers and querying experts, yielding five additional relevant studies (Beal & Crockett, 2010; Destin & Oyserman, 2010; Messersmith & Schulenberg, 2008; Muller, 2001; Oyserman et al., 2021). In total, we found 20 longitudinal studies that measured both possible identities and subsequent academic outcomes. We summarize these studies in Table 1. For interested readers, we list the full set of references our keyword search revealed in Supporting Information Materials.

In the top panel of Table 1, we summarize 10 studies that are similar in four ways. (a) They use secondary data analyses of large-scale data sets. (b) They measure academic attainment as graduating high school, enrolling in college, or graduating college—students report the highest level of education they think they will get (Feliciano, 2012) or their likelihood of going to college (Schoon & Ng-Knight, 2017).[1] (c) They assess school-focused possible identities with a single item (e.g., students respond to a closed-ended question of how far they expect to go in school or whether they expect to go to college). (d) Participants are in high school (in the United States, Australia, and England). Researchers generally obtain data about expectations when students are in high school and measure their educational outcomes years later. The exception is Webb et al. (2002), who assessed if 13-year-olds who scored in the top 1% in standardized math and science tests and said that they expected to complete a science or math major did graduate in math or science and take math- or science-related jobs. Across studies, the high school possible identities response predicts educational attainment multiple years later. The weakness of these studies is that it is impossible to parse a single item possible identity measure for the underlying process. When students report expecting to attain college, are effects on subsequent academic and educational attainment due to possible identity valence (presence or absence of positive expectations), possible identity content (about school), or some other aspect of possible identities associated with content and valence?

We found two studies that use multi-item measures of possible identities—that can help address this problem (and middle school participants, Anderman et al., 1999; Zhoc et al., 2019). We summarize these studies in the second panel of Table 1. Zhoc et al. (2019) used five 3-item scales to ask 7th- and 8th-grade Hong Kong Chinese students about their career, society, family, wealth, and fame-related future goals. Students who agreed more with the career-focused and society-focused items and less with the family- and fame-focused ones scored higher on a standardized English and Math test 12 months later. Anderman et al. (1999, Study 1) asked US 7th-graders about their future academic (being a good student, smartest in class, doing better than other students, and on the honor roll) and social identities (popular, chosen first for teams and groups, have many friends, and competitive). Both scores predicted end-of-year grade point averages (GPAs). Only academic possible identity scores predicted change in GPA. These results imply that content and valence may jointly matter but do not consider the effect of possible identity structure. The weakness of these studies is the close-ended nature of possible identity measures—we can only assess agreement or disagreement with ideas presented by researchers.

We found eight studies that address this weakness; they use open-ended measures of possible identities and strategies in 8th grade to test the effects on subsequent grades or standardized test scores (a year or more later). They use a mixed methods approach to quantify open-ended responses to next-year positive (expected) and negative (to-be-avoided) possible identity probes (except Destin & Oyserman, 2010; who asked for 10-year future job possible identities). After describing their possible identities, student note if they are doing anything to work on these possible identities, and if so, list their strategies (except Oyserman et al., 1995, Study 4, who did not ask students to report their strategies). We summarize these studies in

[1] Variations are slight. Some researchers code college responses as a binary (expect to go to college, yes/no, Merolla, 2013; Ou & Reynolds, 2008). Marjoribanks (2003) collects aspiration data twice, separated by a year, and uses an average. Beal and Crockett (2010) ask about and separately report the effects of aspired education and occupation (coded for occupational prestige).

TABLE 1 Possible identities and academic outcomes: Operationalizations in studies linking possible identities to later academic outcomes

Study characteristics				Predictor focuses on			
Author(s)	Year	N	Possible identity predictor	Valence	Content	Structure	Academic outcome
Studies using Expected Educational Attainment (EEA) as a single-item close-ended predictor measure							
Beal & Crockett[a]	2010	317	EEA, "What kind of work would you like to do?"		√		Educational attainment
Feliciano	2012	3611	EEA		√		Grades
Merolla	2013	5948	EEA		√		HS graduation, enroll postsecondary
Messersmith & Schulenberg	2008	12,066	EEA		√		Attain a BA
Muller	2001	3422	EEA		√		12th grade Math proficiency (not math proficiency growth from 10th grade)
Ou & Reynolds	2008	1286	EEA		√		Graduate HS, years in school
Schoon & Ng-Knight	2017	5770	EEA		√		Standardized test scores, College enrollment
Mattern & Shaw	2010	107,453	EEA		√		SAT scores; 1st-year undergrad GPA.
Marjoribanks[b]	2003	8322	EEA asked twice		√		Educational attainment
Webb et al.[c]	2002	1112	Expected undergraduate major		√		Attain a math/science-related degree, work in a math/science-related job
Studies using multi-item close-ended measures of academic possible identities							
Anderman et al.	1999	315	Academic and social possible identities (four items each)	√	√	√	Grades
Zhoc et al.	2019	8354	3-item career, society, family, wealth, fame goals		√		Standardized exam (English, Math)
Studies using open-ended measures of academic possible identities							
Bi & Oyserman, Study 3	2015	176	Possible identities with strategies (count)		√	√	National exam score
Bi & Oyserman, Study 4	2015	145	Possible identities with strategies (count)		√	√	National exam score
Destin & Oyserman Study 1	2010	266	Education-dependent adult identities (count)		√		Grades
Horowitz et al.	2020	247	School-focused possible identities (count, balance, plausibility)	√	√	√	Grades
Oyserman et al.	2004	160	School-focused possible identities (count, balance, plausibility)		√	√	Grades
Oyserman et al.	2006	264	School-focused possible identities (balance, plausibility)	√	√	√	Grades

TABLE 1 (Continued)

Study characteristics				Predictor focuses on			
Author(s)	**Year**	***N***	**Possible identity predictor**	**Valence**	**Content**	**Structure**	**Academic outcome**
Oyserman et al.	2021	1142	Machine-scored possible identities	√	√	√	Grades, course failure
Oyserman et al., Study 4	1995	44	Balanced school-focused possible identities (count)	√	√	√	Grades

Note: The Cohen's *f*2 effect sizes we could calculate are: Beal & Crockett (2010) (0.15); Bi & Oyserman (2015) Study 3 (0.08), Study 4 (0.06); Horowitz et al. (2020) (0.03–0.05); Oyserman et al. (2004) (0.03–0.04); and Marjoribanks (2003) (0.10). Analyzed secondary datasets are: (1) the children of immigrants (Feliciano, 2012). (2) Longitudinal surveys of Australian Youth (Marjoribanks, 2003). (3) College Board (Mattern & Shaw, 2010). (4) National Educational Longitudinal Study (Merolla, 2013, Muller, 2001). (5) Monitoring the Future (Messersmith & Schulenberg, 2008). (6) Chicago Longitudinal Study (Ou & Reynolds, 2008). (7) Longitudinal Study of Young People in England (Schoon & Ng-Knight, 2017). We excluded studies assessing academic expectations rather than outcomes (Cunningham & Swanson, 2010) or academic overconfidence rather than outcomes (Beyer, 1999; De Paola et al., 2014; Landrum, 1999; Manger & Teigen, 1988; Svanum & Bigatti, 2006; Timmons 2019; Wendorf, 2002). We excluded Marjoribanks 2004, 2005, who analyzed the same data set as Marjoribanks, 2003, and Cadely and colleagues (2011) who assessed the concurrent rather than the not lagged association between possible identities and attainment.

Abbreviations: BA, Bachelor of Arts; EEA, expected educational attainment; HS, high school; √, Yes; empty, No.

[a]Beal & Crockett report separate analyses for each item.

[b]Marjoribanks measured expectation in 1996 and 1997 and, in 2000, measured 1 = did not complete secondary school; 6 = studying for a university degree.

[c]Webb et al. sampled 18-year-olds planning a math or science major.

the bottom panel of Table 1. Each study uses mixed methods, quantifying open-ended measures. The studies differ in what exactly is quantified. Some focus on the valence, others on the content or structure of possible identities (participants are middle school students in the United States, e.g., Destin & Oyserman, 2010; Oyserman et al., 2004, 2006; and China, e.g., Bi & Oyserman, 2015). Most studies use human coders (Bi & Oyserman, 2015). Some train a machine algorithm to capture aspects of human coding (Horowitz et al., 2020; Oyserman et al., 2021). Results suggest that some combination of possible identity content (about school), valence (includes both positive and negative aspects), and structure (linked to strategies) likely matters. Two studies code for multiple aspects of a possible identity: Oyserman et al. (2004) suggest possible identity structure, assessed with plausibility scores, as the best predictor of subsequent academic outcomes (assessed as GPA controlling for past grades). Horowitz et al. (2020) suggest that a machine algorithm can model human coding and allow researchers interested in possible selves to score them at a scale of the size used in studies employing a single-item measure. These studies suggest we focus on capturing how students describe their possible identities.

2 | THE CURRENT STUDIES

We employ machine learning and network analysis to address the key question of capturing possible identities in their complexity at scale. Our approach yields four advances. First, we replicate the prior finding that possible identities predict academic outcomes using a scalable machine algorithm to capture the complexities of possible identities. Second, we document that changes in our possible identity-based machine scores predict changes in GPA over time. Third, we examine the relationship among posited possible identity mechanisms. Fourth, we document that our machine score captures both balance and plausibility and has the advantage of being applicable at scale when human coding is impractical.

2.1 | Participants, power, and open access

Machine learning requires a large, rich data set for informative and generalizable algorithms (e.g., Sordo & Zeng, 2005). Hence, we use larger data sets ($N_1 = 602$, $N_2 = 540$) for training and our smaller one ($N = 247$) to evaluate predictive power. For a priori power analysis, we use a Bayesian approach focused on precision—highest probability density (HPD) credible intervals. HPD intervals have a 95% probability of containing the true value of a parameter given the data. Following Kruschke and Liddell (2018), HPD is the appropriate tool of inference for secondary analysis, while power analysis using error rates is appropriate for estimating power before data collection. We provide code, syntax, the secondary data we are permitted to share and Supplemental Materials at osf.io/m5wpf/?view_only=ec089ea71905413cbda8a35a295df235.

2.1.1 | Analytic strategy

We use a Bayesian approach and the brms package in R (Bürkner, 2017). GPA skews toward higher grades (Chowdhury, 2018), so we assume a generalization of the normal distribution that accounts for skew (skew-normal, Azzalini & Valle, 1996). We use weakly informative priors for all parameters and the Markov Chain Montecarlo method to obtain the posterior distribution and expert recommendations for Bayesian workflow to evaluate model convergence (Gelman et al., 2008, 2020; Supporting Information Materials detail priors and model convergence). We report regression coefficients for the predictors and the 95% highest HPD credible intervals for model parameters at each step. We infer effects when model coefficient credible intervals do not include zero. Following Vehtari et al. (2016), we report leave-one-out cross-validation and Watanabe–Akaike information criteria indices of model fit (smaller numbers indicate better fit, for details, Tables S2–S10, Supporting Information Materials). Data came from Department of Education grants (training samples 1 and 2, Grant #U411C150011, IRB #HS-AT-00646; test sample, Grant #R305A140281, IRB #UP-14-00287). Training sample data were not previously published. We use the possible identity balance and plausibility scoring of the test sample data made available by Horowitz et al. (2020).

3 | STEP 1

3.1 | Participants

Table 2 summarizes our sample demographics. At Step 1, our training sample participants were aged 14.5 on average and attended mid-low poverty schools in Colorado. Our test sample participants were aged 13 on average and attended high-poverty schools in Illinois. We operationalized poverty with the Department of Education definition which focuses on the percentage of students receiving subsidized school meals (High: ≥75%, Mid-high: 51%–75%; Mid-low: 26%–50%; Low: ≤25%).

TABLE 2 Training and test sample demographics

	Training samples		Test sample
Demographics	**Steps 1 and 3**	**Step 2**	**Steps 1, 2, and 3**
N	602	540	247
Median age	14.5	14.5	13
Gender (% female)	47.0	47.1	55.0
% Subsidized school meals	43.6	43.3	92.0
% White	60.1	59.3	2.0
% LatinX	28.0	28.1	84.0
% Black/African American	8.8	9.1	14
% Asian	3.2	3.5	<1
% 7th grade	16.5	18.6	0
% 8th grade	16.0	17.6	100
% 9th grade	36.6	37.9	0
% 10th grade	30.8	25.8	0

Note: Training sample students played a science or language arts game after being randomly assigned to the active control condition in an 11-school randomized controlled development grant (U.S. Department of Education, Grant #U411C150011). The final sample for analysis includes students with parental consent and complete GPA information who were present when the survey was administered ($n = 602$). Test sample students ($N = 502$) were randomly assigned to a school-as-usual control condition in a 7-school development grant (Department of Education, Grant #R305A140281). The final sample for analysis includes students who had parental consent, were present for the fall and spring surveys, and had complete administrative data on 6th- 7th-, and 8th-grade GPA, and demographics ($n = 247$). Step 3 analysis is of the 559 observations from these 247 students.

Abbreviation: GPA, grade point average.

3.2 | Measures

3.2.1 | Demographics and GPA

School districts in Colorado and Chicago provided unweighted current and prior year course grades (0 = F, 1 = D, 2 = C, 3 = B, 4 = A), subsidized meal status, gender, and race/ethnicity as part of data-sharing agreements for training sample 1 (Colorado) and the test sample (Chicago, American Institutes for Research). We computed GPAs by averaging final course grades in Math, Science, English, History, and Social Studies.

3.2.2 | Next-year possible identities and strategies

Training and test sample students responded to an online Qualtrics survey starting with the open-ended possible identities probes. Test sample students completed the possible identities Qualtrics survey at the beginning (first few weeks) and end (9 months later) of the school year. The probes were from Oyserman et al. (2004) and their translations to an online survey were from Horowitz et al. (2020). The full questions are presented in Appendix A, Figure A1. Figure 1 shows the four steps of the possible identities measure—each step occurred on a different screen in the Qualtrics survey.

3.2.3 | Machine algorithm based on possible identity and strategy responses

We used Word2Vec (Mikolov et al., 2013) to train an algorithm to score possible identities and strategies based on their functional relationship with student GPA. Word2Vec quantifies text meaning and structure based on how words co-occur in Google's corpus of news articles written in English, capturing 300 features. We cleaned and preprocessed responses then used the numeric inputs from our Word2Vec and the e1071 package in R (Dimitriadou et al., 2008) to train models with support vector regression, using the 300-dimensional representation of student responses to predict end-of-year GPA. We used grid-search and 10-fold cross-validation methods to select a final model (as suggested by Bergstra & Bengio, 2012; Supporting Information Materials provide technical details). Our final model, a machine algorithm GPA prediction score based on possible identity inputs, ranged from 0 to 4. We computed test sample scores for fall ($M = 2.95$, $SD = 0.14$) and spring ($M = 2.93$, $SD = 0.15$) to obtain a residual change score, $M = -0.003$, $SD = 0.146$, $Min = -0.56$, $Max = 0.26$, for analysis.

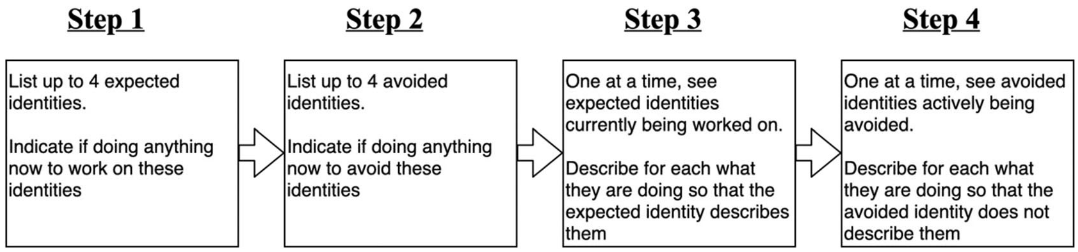

FIGURE 1 Four screens guided participants to describe their possible identities and strategies.

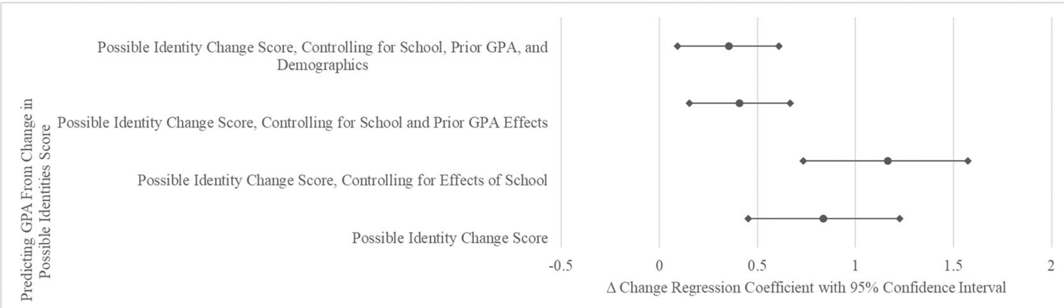

FIGURE 2 Change in possible identity scores predicts change in grades with (top) and without (bottom) covariates. Diamonds at the ends of each line segment are 95% credible intervals, and circles in each line segment represent means. Line segments to the right the 0 imply positive effects of change in possible identity scores on GPA. GPA, grade point average.

3.3 | Results and discussion

When students' possible identity scores improved, so did their GPA—as revealed in the four-step Bayesian regression equation we displayed graphically in Figure 2 (Table S2, Supporting Information Materials). We looked first at the main effect of possible identity change scores on change in GPA ($b = 0.84$, CI [0.453, 1.225]; $R^2 = 0.03$, 95% Credible Interval [0.005, 0.055]). The Credible Interval does not include 0, implying that when identity scores change for the better, so does GPA (Figure 2, base panel). Effects are stable when we added controls as shown in Figure 2, proceeding from the bottom. Thus, effects remain when controlling for (a) attending a particular school, Δ possible identity score $b = 1.17$, CI [0.734, 1.573], (b) prior GPAs (6th- and 7th-grade GPA) in addition to school effects, Δ possible identity score $b = 0.41$, CI [0.155, 0.668], and (c) student descriptors (gender, race-ethnicity, receipt of subsidized school meals, in addition to school and GPA effects), Δ possible identity score $b = 0.35$, CI [0.093, 0.611]. Identity change is central to dynamic theories of self-concept (Frazier et al., 2021; Kaplan & Garner, 2020; Oyserman et al., 2012) but prior studies fail to assess possible identity change as a predictor of GPA (see though Horowitz et al., 2020). We assess possible identities with a multidimensional measure and document that change in possible identities affects grades.

4 | STEP 2

In Step 2, we developed a control algorithm not based on possible identity and strategy responses to use as a control to test the stability of our possible identities algorithm in a way that addresses a limitation of machine learning, which is that scores might capture extraneous differences (Rudin et al., 2018).

4.1 | Participants

Students ($n = 540$, Table 2) in training sample 2 were from the same student population as training sample 1. The two samples are not identical because attendance varied across days.

4.2 | Measures

We used the procedure we outlined in Step 1 to produce a "control" algorithm using a second writing sample that did not focus on possible identities. We present the writing probes in Appendix B, Table B1. We applied this algorithm to possible identity responses to create a residual score representing changes in how students write about their possible identities ($M = 0.00$, $SD = 0.036$, $Min = -0.18$, $Max = 0.05$). Administrative records provided subsidized meal status, gender, race/ethnicity, 6th- and 7th-grade GPA (controls) and 8th-grade GPA (outcome).

4.3 | Results and discussion

We present our results graphically in Figure 3 and full regression results in Table S3 Supporting Information Materials. Line segments crossing the zero point imply no significant effect on GPA, we see this for the control algorithm (no student controls, bottom line segment; with student controls, second line segment from the top). Line segments to the right of the zero point imply positive predictive power—a significant effect on GPA. We see this for our possible identity-based algorithm—the second line segment shows the effect of our algorithm controlling for the nonpossible-identity-based algorithm; the top line segment shows its effect when controlling for school, prior GPAs, and demographics. We infer that when students' possible identities change, so do their GPAs. Our method provides a scalable way to score possible identities that accounts for identity complexity.

5 | STEP 3

In Step 3, we address another limitation of machine scores, their opaqueness, by examining which possible identity measures are associated with these scores and by applying a novel network analysis technique to explore the possibility of additional structural aspects of possible identities that can be accounted for using this multidimensional method.

5.1 | Sample

Our test sample participants (fall $n = 301$, spring $n = 271$) were aged 13 on average and attended high-poverty schools (see Table 2 for demographics, sample size varies due to attendance on the days the survey was completed).

5.2 | Measures

We already explained how we generated our machine-algorithm possible identity scores and our GPA outcome measures. Student gender, race/ethnicity, and subsidized school meal status came from administrative records. We obtained our

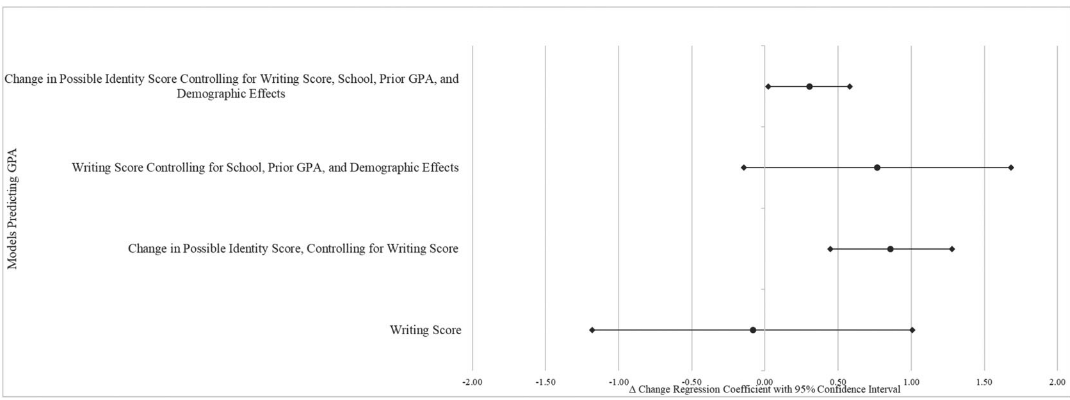

FIGURE 3 Possible identity scores, not control algorithm scores, predict GPA: possible identity algorithm scores are capturing signal. Diamonds at the ends of each line segment are 95% credible intervals, and circles in each line segment represent means. Line segments to the right the 0 imply positive effects of change in possible identity scores on GPA. The writing score is our control algorithm with and without controls, this does not predict grades (line segments overlap 0). The possible identities score in this sample does predict GPA, controlling for writing score and the full set of covariates. GPA, grade point average.

school-focused balance scores and school-focused plausibility scores from Horowitz et al. (2020). In Table 3 we provide descriptive information on our network-based constructs. To create these, we first created a dictionary-reduced set of possible identity and strategy responses (Appendix C for full dictionary, Table C1, and coding process, Figure C1). Then we used the igraph package (Csardi & Nepusz, 2006) to derive student-level Fall and Spring network graphs based on these. We calculated word/concept count, school word/concept count, school hub, and school bridge scores from these graphs. We assessed hubs by counting and then summing the connections in each response network to words/concepts about school. To make scores comparable across response networks of varying sizes, we divided this raw count by the number of unique words in the network minus one (Freeman, 1978). Then we summed these normalized scores to yield a single school hub score. We normalized bridge scores by summing the nonnormalized betweenness values of words and concepts about school and dividing this sum by the largest possible value of betweenness for a single word/concept in a network ($M = 1.87$, $SD = 1.11$).

5.3 | Results and discussion

5.3.1 | Associations among measures of possible identities

As detailed in Table 4, except for hub scores, each aspect of possible identities (valence, balance, and plausibility score) is positively associated with the others. We infer from this that prior results from studies employing a single measure of possible identities might well be capturing other associated aspects of possible identities—explaining what otherwise seems to be a heterogeneous collection of effects.

5.3.2 | Predicting GPA

Results support our inference that prior studies may not have captured sufficient detail in their measures. We found significant effects of balance and plausibility and of having to-be-avoided possible identities but no effect of school-focused possible identity content or positive expected identities on subsequent grades. Thus, students with higher school-focused plausibility, $r(256) = 0.23$, 95% CI (0.11, 0.34), $p < .001$, and balance scores, $r(256) = 0.18$, 95% CI (0.06, 0.30), $p = .004$, and more to-be-avoided negative possible identities, $r(256) = 0.16$, 95% CI (0.04, 0.28), $p = .01$ had higher lagged GPAs. In contrast, having more positive expected possible identities, $r(256) = 0.083$, 95% CI (−0.04, 0.20), $p = .18$, more

TABLE 3 Step 3: Measuring possible identities: Operationalization and descriptive statistics

Aspect Targeted	Operationalization	*M*	*SD*	Range Min	Range Max
Valence					
Positive	# Expected (positive) possible identities	2.88	1.40	0	4
Negative	# Feared (negative) possible identities	2.77	1.44	0	4
School Content	# School-focused words/concepts	1.74	2.08	0	14
Structure					
Balance	# Expected and feared school-focused possible identity pairs	1.18	1.01	0	4
Plausibility	# School-focused possible identities with linked strategies	3.34	1.55	0	5
Network hub	Score from the network analysis of school-focused content centrality	0.79	0.49	0	4
Network bridge	Score from the network analysis of school-focused content bridges	1.87	1.11	0	5.26

Note. Valence = The number of (4 max) expected ($M = 2.88$, $SD = 1.40$) and feared possible identities ($M = 2.77$, $SD = 1.44$). Content = Number expected ($M = 2.34$, $SD = 1.13$) and feared ($M = 1.44$, $SD = 1.15$) school-focused possible identities. We obtained our balance and plausibility scores from Horowitz et al. (2020). Balance scores (Oyserman et al., 1995) = the count of the pairs of positive (expected, e.g., "getting good grades") and negative (feared, e.g., "not flunking classes") possible identities that are school-focused ($M = 1.18$, $SD = 1.01$). Horowitz et al. (2020) double-coded all responses and discussed inconsistent codes to an agreement. Plausibility scores (Oyserman et al., 2004) = the extent school-focused possible identities were connected to strategies that could plausibly yield their desired result. Two raters used the Oyserman et al. (2004) rubric to score responses on a scale from 0 (no or one school-focused possible identities without strategies) to 5 (4+ school-focused possible identities with 4+ linked strategies and ≥1 strategy that considers interpersonal aspects of the school context (e.g., "getting along with teachers"). Horowitz et al. (2020) reported good inter-rater agreement, Cohen's Kappa = 0.96; % Agreement = 88%. Bridging scores = summed proportion of shortest paths between two words/concepts in the network passing through a particular node. Bridging reflects how school words and concepts connect other words/concepts in the network (Freeman, 1978). Bridging scores can be >1 for students who wrote school-relevant content in multiple ways, those nodes were at or near the theoretical maximum value of bridging in the network. Hub scores = Number words/concepts in possible identity responses connected to school words/concepts like spokes on a hub, the $M = 0.79$ implies that in a typical student response, school words/concepts connected to 79% of the other words/concepts. Hub scores >1 imply many highly connected school words connected to the same nodes.

school-focused possible identities, $r(256) = 0.05$, 95% CI (−0.07, 0.17), $p = .44$, or more school-content centered in hub-based ($r[256] = -0.09$, 95% CI (−0.21, 0.03], $p = .17$) or bridge-based ways ($r[256] = 0.11$, 95% CI [0.01, 0.23], $p = .07$) did not significantly predict lagged GPAs.

5.3.3 | Predicting machine-based possible identity scores

Next, we examined each possible identity predictor of our machine-based score by conducting sets of Bayesian multilevel regressions with fall and spring observations nested within students (Tables S4–S10, Supporting Information Materials). We depict our results in Figure 4. The y-axis shows the predictors, and the x-axis shows the relationship with the machine-based algorithm score. Line segments are credible intervals—line segments to the right of zero represent significant positive effects, while line segments including zero represent null effects. We find positive relationships for possible identity valence (expected, to-be-avoided), structure (balance, plausibility), and the bridging aspect of network structure. Our machine algorithm score was associated with each of these. We find null effects for school-focused content and a hub-like structure—our machine score was not associated with these. Given the overlap between the aspects of possible identities that are (a) associated with subsequent grades (as described in the prior section) and (b) associated with our machine algorithm, we infer that our machine algorithm has some validity and adds value. That is, it correlates with multiple possible identity measures that predict academic outcomes and yields a distinct operationalization that is scalable when hand coding is not feasible. At the same time, our algorithm is not highly overlapping with any single aspect of possible identities (as detailed in Tables S4–S10, significant R^2 ranges from variance explained of 0.05 for balance and to-be-avoided possible identity scores to 0.08 variance explained for plausibility scores).

TABLE 4 How features of possible identities covary

Variable	1	2	3	4	5	6
1. Count school-focused possible identities	–					
2. Count avoided identities	.13**	–				
3. Count expected identities	.13**	.69**	–			
4. Plausibility score	.30**	.42**	.39**	–		
5. Balance score	.35**	.40**	.34**	.69**	–	
6. School as a bridge	.33**	.20**	.15**	.55**	.47**	–
7. School as a hub	.35**	−.13**	−.15**	.30**	.33**	.53**

**$p < .01$.

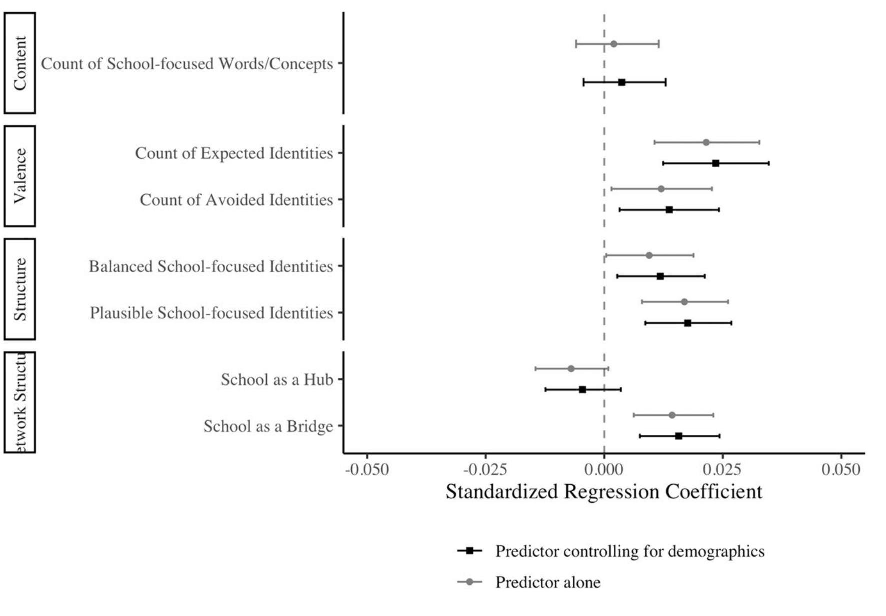

FIGURE 4 The association between aspects of possible identities and our possible identity machine score: Gray circle line segments represent main effects and black square line segments represent effects including demographic controls.

6 | GENERAL DISCUSSION

We showed that various measures of possible identities are correlated but only some (balance, plausibility, to-be-avoided possible identities, our machine algorithm) predict subsequent changes in GPAs. Possible identity structure matters—having school-focused possible identities that are balanced and score high in plausibility by being linked to strategies for action but not school-focused content per se.

6.1 | Synthesis with prior research

The idea of possible selves has cross-cultural appeal as evidenced by the fact that we found studies describing the possible identities of middle and high school students all over the world (e.g., Argentina: Molina et al., 2017; China: Bi & Oyserman, 2015; England: Papafilippou & Bathmaker, 2018; Germany: McElvany et al., 2018; Iran: Mousavi, 2018; Taiwan: Hung & Marjoribanks, 2005). Our results are relevant to theory and interventions focused on the motivational power of possible identities. Helping students leverage their possible identities effectively is central to interventions that improve middle school students' academic outcomes (Oyserman et al., 2021). Intervention researchers and school-based interventions often invoke change in possible identity content as the active ingredient underlying school outcome improvements. Some assess intervention effects on possible identities (e.g., Mackay, 2019; Schlegel et al., 2019), while others assert possible identities as active ingredients without measuring them (e.g., Eichas et al., 2018; Lee et al., 2015; Woolley et al., 2013). This may be due to difficulties assessing complex changes in possible identities. We address this gap by providing a machine-coding algorithm for measurement and showing that possible identity change can be assessed and that change in structure matters—content alone is not enough.

Our review of the longitudinal literature revealed an effect (possible identities predict subsequent academic outcomes) and a gap (a seeming heterogeneity of underlying processes). To make progress, we synthesized IBM theory (Oyserman & Horowitz, in press; Oyserman et al., 2017) with memory, cognition (Bargh & Chartrand, 2014; Collins & Loftus, 1975; Loersch & Keith Payne, 2016), and network science (e.g., Siew et al., 2019). Our synthesis led us to infer that simply having a possible identity would not be enough to increase the odds that it would be repeatedly brought to mind and experienced as apt and actionable (Oyserman & Packer, 1996). We identified aspects of possible identities that might predict subsequent grades, building on prior reviews of the possible identity literature (e.g., Oyserman & James, 2009; Oyserman & Horowitz, in press).

We identified as candidates the number of school-focused possible identities, possible identity valence (number of expected and to-be-avoided possible identities), balance, and plausibility scores (e.g., Oyserman et al., 2004, 2015). Balance scores reflect the number of pairs of expected and to-be-avoided school-focused possible identities a student describes. Balance could increase accessibility and aptness by increasing the likelihood that the way a school-focused possible identity was conceptualized—as preventing failure or promoting success, would be relevant to the features of the situation (Oyserman et al., 2015; see also Higgins, 2005). Plausibility captures the content and valence of possible identities but also includes an action component, the extent to which school-focused possible identities link to concrete strategies—including ones focused on the social context of school (see Oyserman et al., 2004). Students with higher plausibility scores have a roadmap linking school-focused possible identities to concrete strategies for action. The assumption is that once a school-focused possible identity comes to mind, so will relevant strategies for action. We also built on the network literature (Freeman, 1978) to explore whether bridge and hub aspects of the centrality of school-focused content in possible identity networks might matter. Congruent with prior possible identity studies (e.g., Oyserman et al., 2004), we found that possible identity content alone does not predict later GPA. Rather, possible identity valence, balance, plausibility, and our newly developed machine algorithm each predict change in GPA.

6.2 | Limitations, future directions, and concluding comments

Like any study, ours has limitations and leaves some questions unanswered. Here, we focus on culture-based generalizability and our outcome and predictor data. We trained and tested our machine-scoring algorithm in samples of students that varied in race/ethnicity, socioeconomic status, developmental phase, and geographic location. Hence our algorithm-based scoring approach is likely to generalize to other American contexts. We cannot address generalizability outside the United States. However, we found many studies applying the idea of possible identities in an array of societies outside the United States. This implies that future research is needed to study processes outside the United States and potentially outside Western countries. We believe that this research might find that people living in non-Western countries may be more likely to have possible identities that facilitate attaining their school goals. Our results lead us to infer that people who chronically engage in connected reasoning about the self may have practice in making connections, so balance, plausibility, and bridging are likely to be more common aspects of their possible identities. Cultural psychologists describe connected reasoning of this sort as interdependent (Hamedani & Markus, 2019) or collectivistic (Oyserman, 2017) reasoning style. Future research could elaborate on how culture-based knowledge structures how people create and apply their possible identities.

Turning to our outcome measure, we used GPA because it is a real-world outcome with real consequences for students' lives and tends to be measured similarly across American school contexts. However, our literature review revealed stronger associations between possible identities and years of schooling than between possible identities and GPA. Possible identities may contribute more to staying in school than to GPA. Future studies could consider using standardized test scores or subsequent school enrollment. Finally, we used open-ended probes to create our machine algorithm, which provided a rich ideographic basis for our algorithm. Our literature review revealed that most studies use close-ended measures, and almost half use single items as their measure. While not yet prevalent in this literature, future research could increase the richness of the data by including daily-diary or experience sampling results.

Our results support the prediction that school-focused possible identities matter for school outcomes and clarify how. Neither possible identity content nor its centrality alone is sufficient, though both are associated with what matters, which is how possible identities are organized in memory. Students are more likely to do well academically if their possible identities are structured so that an array of strategies for action come to mind when these identities are triggered. This structural feature makes it more likely that school-related action feels identity-congruent, a "me" thing to do, no matter what else comes to mind, and may help keep students focused on their goals no matter the distractions of their setting or context.

AUTHOR CONTRIBUTIONS

Daphna Oyserman: Conceptualization, funding acquisition, investigation, supervision. **S. Casey O'Donnell**: Data curation, formal analysis, methodology, visualization. Writing original draft was a collaboration between the two authors, Daphna Oyserman conducted the revision, review, and final editing.

ACKNOWLEDGMENT

This research was supported in part by the Department of Education (McRel & Oyserman #U411C150011, Oyserman & Sorensen #R305A140281). We thank McRel for developing a data sharing agreement (U411C15001), the American Institutes for Research for developing a data-sharing agreement with Chicago Public Schools, Colorado and Chicago Public Schools for their commitment to improving education through research, Nick Sorensen, and the USC IBM lab for their helpful comments on drafts of this manuscript. We thank Mark Lai, Sarah Townsend, Norbert Schwarz, and Leor Hackel for their critique of that early effort.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The sharable data are available at osf.io/m5wpf/?view_only=ec089ea71905413cbda8a35a295df235.

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REFERENCES

Amodio, D. M. (2019). Social cognition 2.0: An interactive memory systems account. *Trends in Cognitive Sciences*, *23*(1), 21–33.

Anderman, E. M., Anderman, L. H., & Griesinger, T. (1999). The relation of present and possible academic selves during early adolescence to grade point average and achievement goals. *The Elementary School Journal*, *100*(1), 3–17.

Azzalini, A., & Valle, A. (1996). The multivariate skew-normal distribution. *Biometrika*, *83*(4), 715–726.

Bamakan, S. M. H., Nurgaliev, I., & Qu, Q. (2019). Opinion leader detection: A methodological review. *Expert Systems with Applications*, *115*, 200–222.

Bargh, J., & Chartrand, T. (2014). The mind in the middle: A practical guide to priming and automaticity research. In H. Reis & C. Judd (Eds.), *Handbook of research methods in social and personality psychology* (pp. 311–344). Cambridge University Press.

Beal, S. J., & Crockett, L. J. (2010). Adolescents' occupational and educational aspirations and expectations: Links to high school activities and adult educational attainment. *Developmental Psychology*, *46*(1), 258–265.

Benedek, M., Kenett, Y. N., Umdasch, K., Anaki, D., Faust, M., & Neubauer, A. C. (2017). How semantic memory structure and intelligence contribute to creative thought: A network science approach. *Thinking & Reasoning*, *23*(2), 158–183.

Bergstra, J., & Bengio, Y. (2012). Random search for hyper-parameter optimization. *Journal of Machine Learning Research*, *13*(2), 281–305.

Beyer, S. (1999). Gender differences in the accuracy of grade expectancies and evaluations. *Sex Roles*, *41*(3), 279–296.

Bi, C., & Oyserman, D. (2015). Left behind or moving forward? Effects of possible selves and strategies to attain them among rural Chinese children. *Journal of Adolescence*, *44*, 245–258.

Bodenhausen, G., Macrae, C., & Hugenberg, K. (2003). Social cognition. In I. Weiner (Ed.), *Handbook of psychology* (5, pp. 257–282). Wiley.

Bürkner, P. C. (2017). Brms: An R package for Bayesian multilevel models using stan. *Journal of Statistical Software*, *80*(1), 1–28.

Cadely, H. S. E., Pittman, J. F., Kerpelman, J. L., & Adler-Baeder, F. (2011). The role of identity styles and academic possible selves on academic outcomes for high school students. *Identity*, *11*(4), 267–288.

Chowdhury, F. (2018). Grade inflation: Causes, consequences and cure. *Journal of Education and Learning*, *7*(6), 86–92.

Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. *Psychological Review*, *82*(6), 407–428.

Csardi, G., & Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal, Complex Systems*, *1695*(5), 1–9.

De Paola, M., Gioia, F., & Scoppa, V. (2014). Overconfidence, omens and gender heterogeneity: Results from a field experiment. *Journal of Economic Psychology*, *45*, 237–252.

Destin, M., & Oyserman, D. (2010). Incentivizing education: Seeing schoolwork as an investment, not a chore. *Journal of Experimental Social Psychology*, *46*(5), 846–849.

Dimitriadou, E., Hornik, K., Leisch, F., Meyer, D., & Weingessel, A. (2008). Misc functions of the Department of Statistics (e1071), TU Wien. R package, *1*, 5–24.

Eichas, K., Kurtines, W. M., Rinaldi, R. L., & Farr, A. C. (2018). Promoting positive youth development: A psychosocial intervention evaluation. *Psychosocial Intervention*, *27*(1), 22–34.

Feliciano, C. (2012). The female educational advantage among adolescent children of immigrants. *Youth & Society*, *44*(3), 431–449.

Frazier, L. D., Schwartz, B. L., & Metcalfe, J. (2021). The MAPS model of self-regulation: Integrating metacognition, agency, and possible selves. *Metacognition and Learning*, *16*, 297–318.

Freeman, L. C. (1978). Centrality in social networks conceptual clarification. *Social Networks*, *1*, 215–239.

Gelman, A., Jakulin, A., Pittau, M., & Su, Y. (2008). A default prior distribution for logistic and other regression models. *Annals of Applied Statistics*, *2*(4), 1360–1383.

Gelman, A., Vehtari, A., Simpson, D., Margossian, C., Carpenter, B., Yao, Y., Kennedy, L., Gabry, J., Bürkner, P-C., & Modrák, M. (2020). Bayesian workflow. *arXiv preprint arXiv: 2011.01808*.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360–1380.

Hamedani, M. Y. G., & Markus, H. R. (2019). Understanding culture clashes and catalyzing change: A culture cycle approach. *Frontiers in Psychology*, *10*, 700.

Higgins, E. T. (2005). Value from regulatory fit. *Current Directions in Psychological Science*, *14*(4), 209–213.

Horowitz, E., Oyserman, D., Dehghani, M., & Sorensen, N. (2020). Do you need a roadmap or can someone give you directions: When school-focused possible identities change so do academic trajectories. *Journal of Adolescence*, *79*, 26–38.

Hoyle, R. H., & Sherrill, M. R. (2006). Future orientation in the self-system: Possible selves, self-regulation, and behavior. *Journal of Personality*, *74*(6), 1673–1696.

Hung, C. L., & Marjoribanks, K. (2005). Parents, teachers and children's school outcomes: A Taiwanese study. *Educational Studies*, *31*(1), 3–13.

Kang, C., Molinaro, C., Kraus, S., Shavitt, Y., & Subrahmanian, V. (2012). Diffusion centrality in social networks. In *2012 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining* (pp. 558–564). IEEE.

Kaplan, A., & Garner, J. K. (2020). Steps for applying the complex dynamical systems approach in educational research: A guide for the perplexed scholar. *The Journal of Experimental Education*, *88*(3), 486–502.

Kihlstrom, J., & Klein, S. (1994). The self as a knowledge structure. In R. Wyer Jr & T. Srull (Eds.), *Handbook of social cognition: Basic processes* (pp. 153–208). Lawrence Erlbaum.

Kitsak, M., Gallos, L. K., Havlin, S., Liljeros, F., Muchnik, L., Stanley, H. E., & Makse, H. A. (2010). Identification of influential spreaders in complex networks. *Nature Physics*, *6*(11), 888–893.

Kruschke, J. K., & Liddell, T. M. (2018). The Bayesian new statistics: Hypothesis testing, estimation, meta-analysis, and power analysis from a Bayesian perspective. *Psychonomic Bulletin & Review*, *25*(1), 178–206.

Landau, M. J., Oyserman, D., Keefer, L. A., & Smith, G. C. (2014). The college journey and academic engagement: How metaphor use enhances identity-based motivation. *Journal of Personality and Social Psychology*, *106*(5), 679–698.

Landrum, R. (1999). Student expectations of grade inflation. *Journal of Research and Development in Education*, *32*(2), 124–28.

Lee, J., Husman, J., Scott, K. A., & Eggum-Wilkens, N. D. (2015). Compugirls: Stepping stone to future computer-based technology pathways. *Journal of Educational Computing Research*, *52*(2), 199–223.

Loersch, C., & Keith Payne, B. (2016). Demystifying priming. *Current Opinion in Psychology*, *12*, 32–36.

Mackay, D. J. (2019). An ideal second language self intervention: Development of possible selves in an English as a foreign language classroom context. *System*, *81*, 50–62.

Manger, T., & Teigen, K. (1988). Time horizon in students' predictions of grades. *Scandinavian Journal of Educational Research*, *32*(2), 77–91.

Marjoribanks, K. (2003). Learning environments, family contexts, educational aspirations and attainment: A moderation-mediation model extended. *Learning Environments Research*, *6*(3), 247–265.

Marjoribanks, K. (2004). Immigrant adolescents' individual and environmental influences on young adults' educational attainment. *Journal of Comparative Family Studies*, *35*(3), 485–499.

Marjoribanks, K. (2005). Family background, adolescents' educational aspirations, and Australian young adults' educational attainment. *International Education Journal*, *6*(1), 104–112.

Mattern, K. D., & Shaw, E. J. (2010). A look beyond cognitive predictors of academic success: Understanding the relationship between academic self-beliefs and outcomes. *Journal of College Student Development*, *51*(6), 665–678.

McElvany, N., Ferdinand, H. D., Gebauer, M. M., Bos, W., Huelmann, T., Köller, O., & Schöber, C. (2018). Attainment-aspiration gap in students with a migration background: The role of self-efficacy. *Learning and Individual Differences*, *65*, 159–166.

Merolla, D. M. (2013). The net Black advantage in educational transitions: An education careers approach. *American Educational Research Journal*, *50*(5), 895–924.

Messersmith, E. E., & Schulenberg, J. E. (2008). When can we expect the unexpected? Predicting educational attainment when it differs from previous expectations. *Journal of Social Issues*, *64*(1), 195–212.

Mikolov, T., Sutskever, I., Chen, K., Corrado, G., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. In C. Burges, L. Bottou, M. Welling, Z. Ghahramani, & K. Weinberger (Eds.), *Advances in neural information processing systems* (pp. 3111–3119). Curran Associates.

Molina, M., Raimundi, M., & Gimenez, M. (2017). Los posibles sí mismos de los adolescentes de Buenos Aires. *Revista Latinoamericana de Ciencias Sociales. Niñez y Juventud*, *15*(1), 455–470.

Mousavi, H. (2018). The roles of possible selves in Iranian EFL learners' L2 learning motivation. *Journal on English Language Teaching*, *8*(3), 18–28.

Muller, C. (2001). The role of caring in the teacher-student relationship for at-risk students. *Sociological Inquiry*, *71*(2), 241–255.

Nurra, C., & Oyserman, D. (2018). From future self to current action: An identity-based motivation perspective. *Self and Identity*, *17*(3), 343–364.

Oettingen, G., Mayer, D., Thorpe, J. S., Janetzke, H., & Lorenz, S. (2005). Turning fantasies about positive and negative futures into self-improvement goals. *Motivation and Emotion*, *29*(4), 236–266.

Ou, S. R., & Reynolds, A. J. (2008). Predictors of educational attainment in the Chicago longitudinal study. *School Psychology Quarterly*, *23*(2), 199–229.
Oyserman, D. (2007). Social identity and self-regulation. In A. Kruglanski & E. T. Higgins (Eds.), *Handbook of social psychology: Basic principles* (pp. 432–453). Guilford.
Oyserman, D. (2017). Culture three ways: Culture and subcultures within countries. *Annual Review of Psychology*, *68*, 435–463.
Oyserman, D. (2019). The essentialized self: Implications for motivation and self-regulation. *Journal of Consumer Psychology*, *29*(2), 336–343.
Oyserman, D., Bybee, D., & Terry, K. (2006). Possible selves and academic outcomes: How and when possible selves impel action. *Journal of Personality and Social Psychology*, *91*(1), 188–204.
Oyserman, D., Bybee, D., Terry, K., & Hart-Johnson, T. (2004). Possible selves as roadmaps. *Journal of Research in Personality*, *38*(2), 130–149.
Oyserman, D., Destin, M., & Novin, S. (2015). The context-sensitive future self: Possible selves motivate in context, not otherwise. *Self and Identity*, *14*(2), 173–188.
Oyserman, D., Elmore, K., & Smith, G. (2012). Self, self-concept, and identity. In M. R. Leary & J. P. Tangney (Eds.), *Handbook of self and identity* (pp. 69–104). Guilford.
Oyserman, D., Gant, L., & Ager, J. (1995). A socially contextualized model of African American identity: Possible selves and school persistence. *Journal of Personality and Social Psychology*, *69*(6), 1216–1232.
Oyserman, D., & Horowitz, E. (in press). When and how possible selves predict future action. Advances in Motivation Science.
Oyserman, D., & James, L. (2009). Possible selves: From content to process. In K. D. Markman, W. M. P. Klein, & J. A. Suhr (Eds.), *Handbook of imagination and mental simulation* (pp. 373–394). Psychology Press.
Oyserman, D., & James, L. (2011). Possible identities. In S. Schwartz, K. Luyckx, & V. Vignoles (Eds.), *Handbook of identity theory and research* (pp. 117–145). Springer.
Oyserman, D., Lewis, Jr., N. A., Yan, V. X., Fisher, O., O'Donnell, S. C., & Horowitz, E. (2017). An identity-based motivation framework for self-regulation. *Psychological Inquiry*, *28*(2–3), 139–147.
Oyserman, D., & Markus, H. (1990). Possible selves in balance: Implications for delinquency. *Journal of Social Issues*, *46*(2), 141–157.
Oyserman, D., O'Donnell, S. C., Sorensen, N., & Wingert, K. M. (2021). Process matters: Teachers benefit their classrooms and students when they deliver an identity-based motivation intervention with fidelity. *Contemporary Educational Psychology*, *66*, 101993.
Oyserman, D., & Packer, M. (1996). Social cognition and self-concept: A socially contextualized model of identity. In J. Nye & A. Brower (Eds.), *What's social about social cognition? Research on socially shared cognition in small groups* (pp. 175–201). Sage. https://doi.org/10.4135/9781483327648.n8
Paluck, E., & Shepherd, H. (2012). The salience of social referents: A field experiment on collective norms and harassment behavior in a school social network. *Journal of Personality and Social Psychology*, *103*(6), 899–915. https://doi.org/10.1037/a0030015
Papafilippou, V., & Bathmaker, A. (2018). Transitions from higher education to employment among recent graduates in England: Unequal chances of achieving desired possible selves. In H. Henderson, J. Stevenson, & A. M. Bathmaker (Eds.), *Possible selves and higher education* (pp. 123–138). Routledge.
Rudin, C., Wang, C., & Coker, B. (2018). The age of secrecy and unfairness in recidivism prediction. *Science Review*, *2*(1). https://doi.org/10.1162/99608f92.6ed64b30
Ruvolo, A. P., & Markus, H. R. (1992). Possible selves and performance: The power of self-relevant imagery. *Social Cognition*, *10*(1), 95–124.
Schlegel, R., Chu, S., Chen, K., Deuermeyer, E., Christy, A., & Quek, F. (2019). Making in the classroom: Longitudinal evidence of increases in self-efficacy and STEM possible selves over time. *Computers & Education*, *142*, 103637.
Schoon, I., & Ng-Knight, T. (2017). Co-development of educational expectations and effort: Their antecedents and role as predictors of academic success. *Research in Human Development*, *14*(2), 161–176.
Siew, C. S. Q., Wulff, D. U., Beckage, N. M., Kenett, Y. N., & Meštrović, A. (2019). Cognitive network science: A review of research on cognition through the lens of network representations, processes, and dynamics. *Complexity*, *2019*, 2108423.
Sordo, M., & Zeng, Q. (2005). On sample size and classification accuracy: A performance comparison. In J. Oliveira, V. Maojo, F. Martín-Sánchez, & A. Pereira (Eds.), *Biological and medical data analysis* (pp. 193–201). Springer.
Svanum, S., & Bigatti, S. (2006). Grade expectations: Informed or uninformed optimism, or both? *Teaching of Psychology*, *33*(1), 14–18.
Timmons, K. (2019). Kindergarten expectations and outcomes: understanding the influence of educator and child expectations on children's self-regulation, early reading, and vocabulary outcomes. *Journal of Research in Childhood Education*, *33*(3), 471–489.
U.S. Department of Education. (2018). Table 216.60. *Digest of education statistics*.
Vehtari, A., Gelman, A., & Gabry, J. (2016). Practical Bayesian model evaluation using leave-one-out cross-validation and waic. *Statistics and Computing*, *27*(5), 1413–1432.
Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*. Cambridge University Press.
Webb, R. M., Lubinski, D., & Benbow, C. P. (2002). Mathematically facile adolescents with math-science aspirations: New perspectives on their educational and vocational development. *Journal of Educational Psychology*, *94*(4), 785–794. https://doi.org/10.1037/0022-0663.94.4.785
Wendorf, C. (2002). Grade point average and changes in (great) grade expectations. *Teaching of Psychology*, *29*(2), 136–137.
Woolley, M. E., Rose, R. A., Orthner, D. K., Akos, P. T., & Jones-Sanpei, H. (2013). Advancing academic achievement through career relevance in the middle grades: A longitudinal evaluation of CareerStart. *American Educational Research Journal*, *50*(6), 1309–1335.
Zhoc, K. C. H., King, R. B., Law, W., & McInerney, D. M. (2019). Intrinsic and extrinsic future goals: Their differential effects on students' self-control and distal learning outcomes. *Psychology in the Schools*, *56*(10), 1596–1613.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: O'Donnell, S. C., & Oyserman, D. (2022). Apt and actionable possible identities matter: The case of academic outcomes. *Journal of Adolescence*, 1–18. https://doi.org/10.1002/jad.12118

APPENDIX A: POSSIBLE IDENTITIES

See Figure A1.

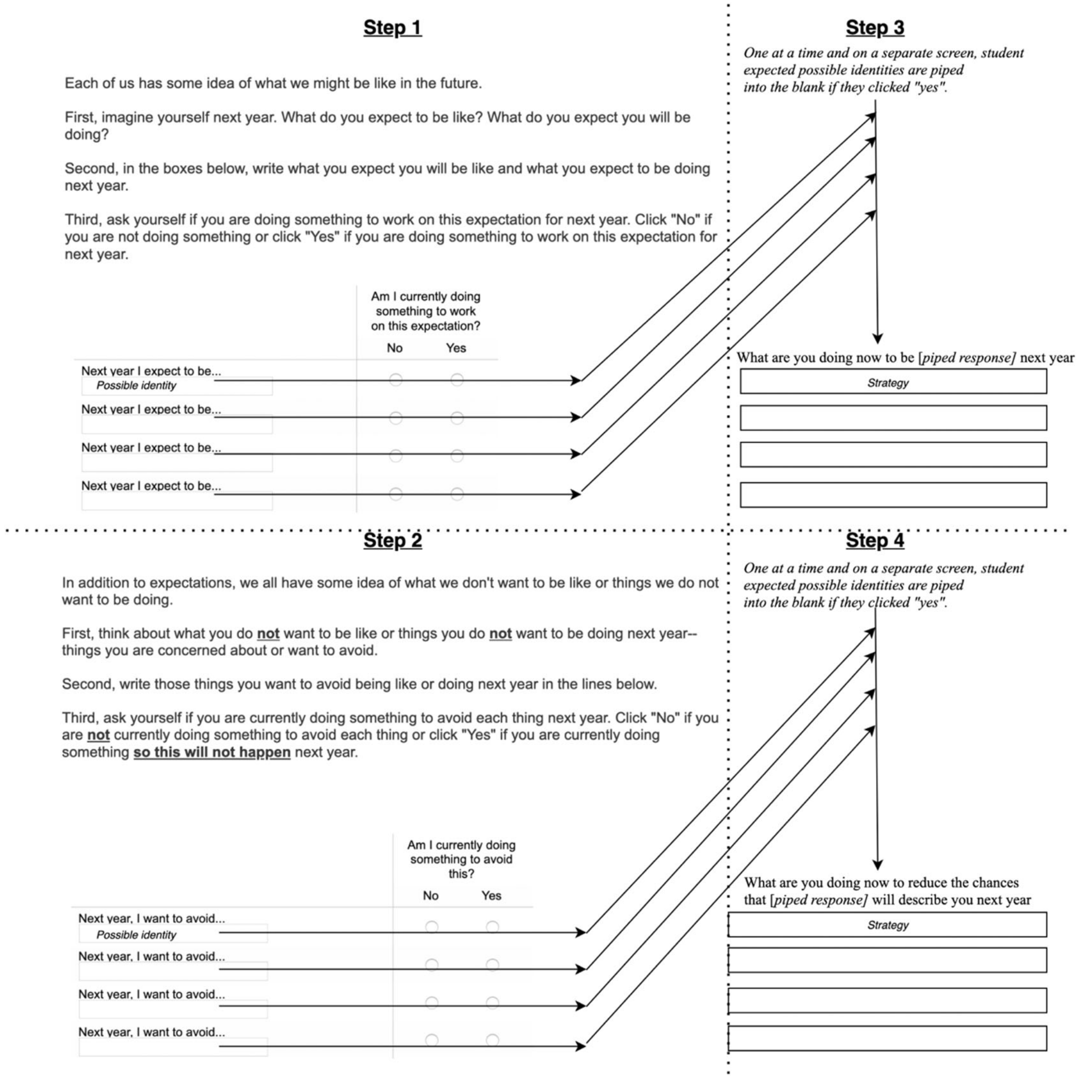

FIGURE A1 The Qualtrics screens for each of the four steps to obtaining possible identities and strategies to work on them.

APPENDIX B: CONTROL WRITING SAMPLE

Table B1 presents the open-ended questions (Table B1) students were asked after playing a computerized science or language arts educational game. We compiled these responses to capture other features of student writing.

TABLE B1 Open-ended questions we used to train a general writing scoring algorithm.

Question	Text
1	When you missed a day, what did your teacher have you do?
2	What was the best part of the digital program you just completed?
3	What was the worst part of the digital program you just completed?
4	Please use the space below to share any other information about your experience participating in the digital program.

APPENDIX C: COMBINING DICTIONARY-BASED AND NETWORK REPRESENTATION TO OPERATIONALIZE POSSIBLE IDENTITIES

We started with uncategorized preprocessed student possible identity and strategy responses (Figure C1, top panel). Then we developed and applied dictionaries to sort words based on their meaning as detailed next (Figure C1, middle panel). We categorized by semantic content (Table C1, for the dictionary) and form—whether it was a noun, verb, or adjective. We used prior work (Oyserman & Markus, 1990; Oyserman et al., 2004) and a two-step iterative snowball procedure to develop dictionaries with good lower-level categorization coverage of the types of words students used (detailed in our Supporting Information Materials). We collapsed similar words into a higher-order concept except when words were common and relevant when considered alone (e.g., we did not collapse homework, the 6th-most common word, into the higher-order concept of school). We represented words as belonging to one of our dictionaries (41% of words) or not. The latter were either idiosyncratic (e.g., "heaven," "youtube") or ambiguous (e.g., "judgment" could refer to being judged by others or using good judgment).

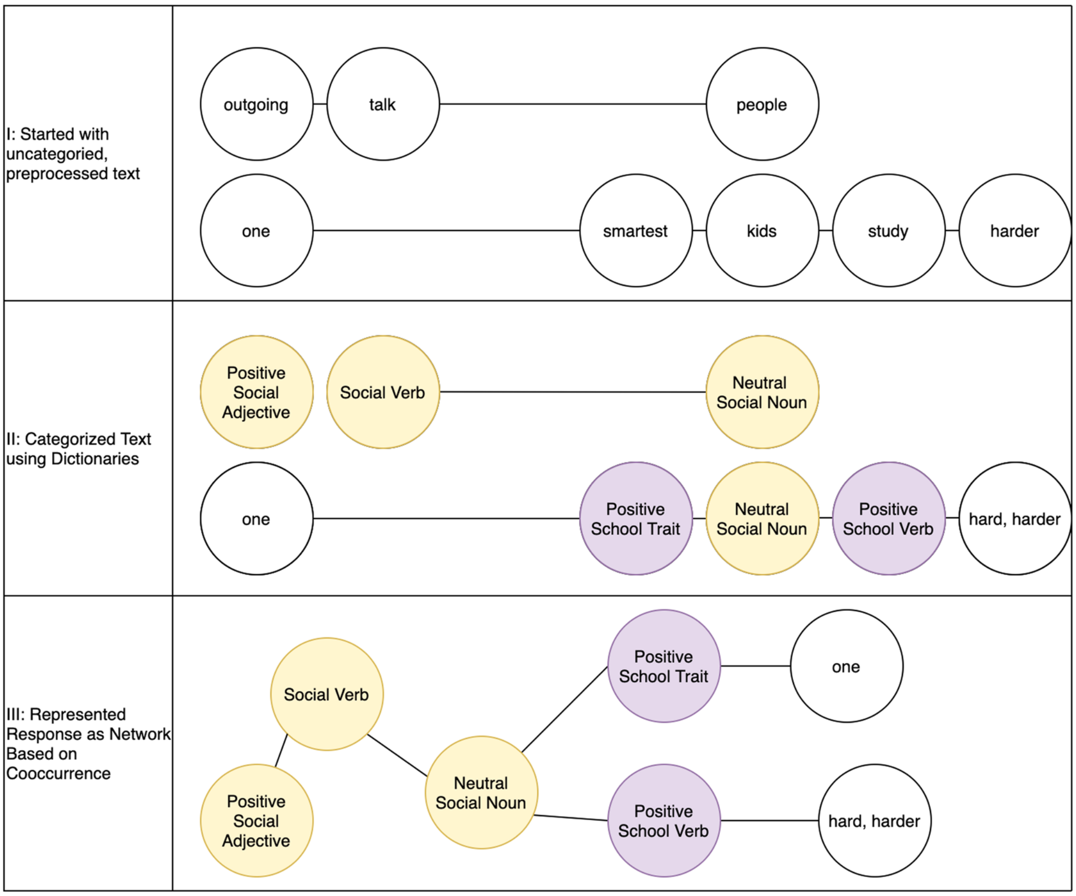

FIGURE C1 Network representation of text. Colors represent superordinate categories. Purple = school-focused words; White = uncategorized words; Yellow = interpersonal-focused words. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE C1 Categories used in network analysis by domain.

Domain, category label, and description	Included words
Health, SPORT_N sport nouns	court, basketball, team, ball, baseball, volleyball, soccer, varsity, athlete, football, player, sport
Health, SPORT_V sport verbs	train, play, dribble, layup
Health, HEALTH_N health nouns	diet, athletic, healthy, unhealthy, milk, water, fat, food, fruit, strong
Health, HEALTH_V health verbs	run, swim, eat, drink, exercise, sleep
Interpersonal, SOC_NEU social nouns neutral	people, kid, crowd, person, peer, boy, girl, classmate
Interpersonal, SOC_NEG social nouns negative	bully, drama, gang, enemy, unfriendly
Interpersonal, FRIEND friendship roles	friend, boyfriend, girlfriend
Interpersonal, FAMILY familial roles	sister, brother, dad, mom, mommy, family, cousin, parent
Interpersonal, SOC_ADJ_POS positive social traits	funny, nice, outgoing, positive, friendly, faithful, patient, helpful, respectful
Interpersonal, SOC_ADJ_NEG negative social traits	annoy, shady, dumb, immature, stupid, fake, rude, angry
Valence, POS positive descriptors	amazing, exceptional, good, awesome, cool, fabulous
Valence, NEG negative descriptors	bad, wrong, poor, atrocious, negative,
Off-track, SUBSTANCE substances	drugs, alcohol, drug, smoking, smoke, beer
Off-track, UNCATEGORIZED OFF-TRACK frequent	trouble
School, GRADES grades	grades, GPA, a's, b's.
School, PASS passing, graduating	graduate, pass
School, FAIL failing	fail, dropout
School, ATTN attention words	focus, attention, listen, concentrate
School, MOTIV motivation words	motivated, effort, hardworking, goal
School, HS high school	freshman, high school, 9th, ninth, sophomore
School, MS middle school	8th, eighth, middle school
School, SCH_ADJ_POS positive school traits	responsible, organized, smart, mature, intelligent, hardworking, determined, scholar
School, SCH_ADJ_NEG negative school traits	laziness, procrastination, distraction
School, SCH_SUB specific subjects	Math, Algebra, Science, English, Calculus
School, BEH_SCH_NEG negative school behaviors	skipping, detention, expulsion
School, BEH_SCH_POS positive school behaviors	reading, studying, writing, learning
School, ADV_CLASS advanced student things	valedictorian, honor, AP, ap, 4.0, A, advance
School, HW_ETC homework, Classwork	homework, assignment, worksheet, classwork
School, TESTS_ETC tests, exams	test, exam, quiz
School, TEACH teacher in multiple declinations	teacher, teach, teacher, teach
School, UNCATEGORIZED SCHOOL not fitting else	college, school, learn, student

Note: Syntax includes stemmed forms and multiple declinations of words.
Abbreviation: GPA, grade point average.