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Celebrating Differences: A Conjoint Analysis of Senior Year Mechanical Engineering Students' Occupational Preferences

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Abstract
Given its ongoing struggles at attaining demographic diversity and its key role in nations' economies, the engineering workforce receives considerable attention from researchers and policymakers. Yet, prior studies and STEM recruitment initiatives have often underemphasized the variety among available engineering jobs and careers. It therefore remains unclear which attributes of engineering work are most salient in shaping students' choices to persist in or depart from engineering pathways. This study introduces a novel conjoint survey experiment conducted with over 1000 senior year mechanical engineering students. This randomized experiment allows the authors to disentangle supply-side and demand-side factors to assess engineering job attributes' marginal influences on students' occupational preferences, as well as to examine these attributes' interaction effects with supply-side factors. Toward strengthening persistence in engineering pathways, findings suggest that broad STEM recruitment initiatives, though potentially advantageous in pre-college years, should give way to more targeted campaigns that increase university students' awareness about key dimensions of variety across engineering work roles.

Keywords Persistence in engineering · STEM · Diversity · Conjoint survey experiment

Introduction

Numerous studies have examined how variation in diverse students' career pursuits shapes the composition of the engineering workforce. Research in this area continues as the profession confronts its limited demographic diversity in the U.S. and elsewhere (e.g., Cech et al., 2011; Hatmaker, 2013; Main et al., 2021; McGee & Martin, 2011; Seron et al., 2016, 2018) and as engineering employers seek to increase retention of candidates with strong interpersonal and leadership skills (Cappelli, 2015; Hartmann et al., 2016; Salzman & Lynn, 2010). A subset of this literature has analyzed students' occupational plans in relation to demand-side phenomena, such as biases in employers' preferences (e.g., Anker,

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1997; Gray et al., 2007; Jackson et al., 2014; Reskin, 1993) and differences in labor demand between engineering and alternate fields for specific skills among engineering candidates (e.g., Shu, 2016; Deming, 2017; Célérier & Vallée, 2019). Other studies, meanwhile, have focused on supply-side processes—students' development of career-related preferences, beliefs, and goals—in explaining differences in students' intentions to work in engineering (e.g., Cech et al., 2011; Correll, 2004; Lichtenstein et al., 2009; Seron et al., 2016; Stevens et al., 2008). The existing literature builds compelling cases that both demand-side and supply-side phenomena can explain variance in the career plans of students in engineering pathways.

Yet, engineering work itself varies considerably (Brunhaver et al., 2013; Craps et al., 2021; Perlow & Bailyn, 1997; Ranson, 2003) and it is unlikely that most candidates are accurately and comprehensively informed about differences in work attributes across possible engineering roles (Manning, 2011). These differences include proportions of time allocated to individualistic work compared to collaborative or coordinative work, the mix of skills employed, and the types of career advancement trajectories available, among many others (Brunhaver et al., 2013; Craps et al., 2021; Perlow & Bailyn, 1997; Ranson, 2003). Nonetheless, existing studies that have examined occupational intentions of candidates in engineering pathways often make implicit assumptions about uniformity of engineering work and about consistency of candidates' conceptions of engineering jobs (Brunhaver et al., 2013; Craps et al., 2021). In the present study, we introduce a research design that avoids these assumptions to examine whether differences in university students' awareness of specific engineering job attributes can explain a portion of the observed variance in job preferences.

In this paper we analyze data from a conjoint survey experiment. This research design allows us to assess how job differences shape undergraduate mechanical engineering seniors' attraction to engineering jobs and to test for interaction effects between student characteristics and job attributes upon job attraction. We sampled participants from a broad set of U.S. engineering schools for the survey experiment, first collecting "pre-treatment" data on key participant-specific variables shown in prior studies to be associated with engineering career intentions. This data collection enabled experimental control and interaction analyses. We then engaged participants in the conjoint survey experiment itself, which involved participants' assignment of preference ratings to a series of randomly manipulated job profiles. The randomization in this experiment allows us to draw causal inferences about how the presence of certain job attributes influences candidates' job preferences. We test several such manipulations corresponding with realistic differences in engineering work documented in literature and reviewed in this paper in *Key dimensions of variation in engineering jobs*. Meanwhile, the pre-treatment data collected for each participant corresponds with explanatory variables from a recent aggregate supply-side model of engineering students' occupational intentions (Magarian & Seering, 2022). The participant data, combined with our experimental manipulation of job attributes, allows us to bring both participant- and job-specific characteristics together in an integrated analysis of occupational preference.

Recent advances in conjoint survey methodology provided the framework for this study's design. Conjoint surveys have long been used in marketing research to assess individuals' preferences toward combinations of product attributes (for reviews, see: Green et al., 2001; Rao, 2014). More recent work by Hainmueller et al. (2014) produced a set of proofs and verification procedures that allow conjoint methods to be used for causal inference of specific attributes' marginal influence on preferences. These advances have expanded conjoint methods' applicability in social sciences research (e.g., Carnes & Lupu, 2016; Hainmueller & Hopkins, 2015; Hankinson, 2018). In this paper, we describe our adoption of this approach for assessing students' job preferences.

As its central question, this study asks whether additional variance in students' preferences for engineering jobs is explained by interactions between student-specific and job-specific characteristics—variance beyond that which is explained by these characteristics' independent effects. In short, we investigate how some engineering students may tend to react differently than others upon being informed of realistic attributes of engineering positions. The student subsets whose preferences we compare possess differing characteristics pertinent to existing supply-side explanations of engineering persistence; for instance, differences in enjoyment in working with mathematics, in strength of professional identity, or in leadership aspirations, among others (see: *Supply-side processes and occupational intentions of engineering students*).

Our study advances the literature on engineering workforce formation by assessing how a lack of awareness of the variation across engineering jobs could influence students' persistence propensities in their field as a whole. With assumptions about sufficiency of students' awareness of engineering work (and of the uniformity of such work itself) intrinsic to much of the existing literature (Brunhaver et al., 2013; Craps et al., 2021), prior research may have been limited in its ability to examine the sensitivity of students' job choices to such awareness gaps. In our present era of expanding varieties of engineering work (Magarian & Seering, 2021), understanding the role of student-job interaction effects on job preferences may be of increased importance toward helping students make informed and satisfying choices about persisting in engineering.

We begin the sections that follow with a review of prior studies on engineering students' occupational intentions at the college-careers transition. We first review supply-side research, summarizing the student-specific variables found to be associated with engineering career intentions. We next discuss key attributes of engineering work that have been found to vary within the profession or toward which there are documented trends of societal misperception. These attributes may constitute areas of inconsistency in students' conceptions of engineering work. For the various job attributes, we develop hypotheses (summarized later in Table 1) reflecting how we expect student-specific characteristics will interact with students' awareness of these attributes. We then describe the empirical methods we used to test those hypotheses and we report our findings. We conclude by discussing implications for researchers studying the formation of the engineering workforce, as well as for educators and employers who develop and recruit this workforce.

Supply-Side Processes and Occupational Intentions of Engineering Students

Recent studies have examined processes underlying the development of students' career interests in engineering. This literature asserts that prior explanations limited to demand-side considerations, while pertinent, are insufficient to explain the career path variation observed among university engineering students (Correll, 2004, p. 94–96). Many researchers have indeed found that labor demand conditions influence career intentions among students in engineering pathways (Bardhan et al., 2013; Lynn et al., 2018; Ryoo & Rosen, 2004; Salzman & Lynn, 2010). Scholars of supply-side processes, however, are interested in how phenomena that act upon individuals—such as social and educational experiences of students before they seek their first full-time job—can explain a portion of the variance

Table 1 Hypotheses examined by survey experiment

Hypothesis 1	Engineering students' anticipation of enjoying work involving mathematics interacts with their informedness about a given engineering job's mathematics intensity to influence their attraction to the job. Students who anticipate enjoying work involving advanced mathematics react more positively (in terms of job preference), on average, than their peers when informed that a job is math-intensive
Hypothesis 2	Engineering students' anticipation of early-career advancement into leadership roles interacts with their informedness about a given engineering job's leadership opportunitues to influence their attraction to the job. Students who anticipate early-career advancement into leadership roles react more positively (in terms of job preference), on average, than their peers when informated that a job includes leadership advancement opportunities
Hypothesis 3	Engineering students' strength of professional identity interacts with their informedness about a given engineering job's commitment expectations to influence their attraction to the job. Students with a comparably stronger professional identity react more positively (in terms of job preference), on average, than their peers when informed that a job includes a commitment duration expectation
Hypothesis 4	Engineering students' satisfaction with creative opportunities in engineering work interacts with their informedness about a given engineering job's commitment expectations to influence their attraction to the job. Students who are comparably more satisfied with creative opportunities in engineering work react more positively (in terms of job preference), on average, than their peers when informed that a job includes a commitment duration expectation
Hypothesis 5	Gender and engineering students' informedness about a given engineering job's social components interact to influence students' attraction to the job. Female engineering students react more positively (in terms of job preference), on average, than their peers when informed that a job centers on collaborative or coordinative work

in students' career intentions, *ceteris paribus*. Supply-side analyses therefore examine influences shaping students' beliefs relevant to their sense of career fit in a discipline.

Research in this area, for instance, has examined how students develop beliefs about their mathematics abilities, finding these beliefs to be associated with career intentions in engineering (Correll, 2001; Eris et al., 2010; Litzler & Young, 2012; Nauta et al., 1998), and finding that women are more likely to underestimate their math abilities than men (net of actual ability) (Correll, 2001; Ellis et al., 2016). Literature attributes this self-assessment bias to the development of gendered cultural beliefs about abilities (Correll, 2001, 2004; Hyde et al., 1990). Further, studies have found a link between higher perceptions of one's mathematics ability and anticipated enjoyment of jobs or tasks involving math (Goetz et al., 2008; Sitzmann et al., 2010). Findings therefore suggest that engineering students who anticipate enjoyment in working with mathematics are more likely, on average, to intend to work in engineering after graduation compared to their peers.

Additional literature has linked education-related social experiences to students' development of a strong professional identity as engineers; for instance, students' experiences being accepted, respected, and engaged as participants in engineering project groups or class activities at school (Cech et al., 2011; Seron et al., 2016, 2018) and students' exposure to faculty members' or mentors' encouragement toward working in their field (Amelink & Creamer, 2010; Lichtenstein et al., 2009). Here, studies find variance among student subsets, such as in women students' differing experiences with perceived fit and acceptance during engineering projects compared to men's (Cech et al., 2011; Seron et al., 2016, 2018) and in differences in engineering faculty-student interactions experienced by students studying at engineering-focused institutions compared to more broadly focused institutions (Lichtenstein et al., 2009). In turn, the literature finds students' intentions to work in engineering to be associated with a higher strength of professional identity (Ayre et al., 2013; Cech, 2015; Cech et al., 2011; Eliot & Turns, 2011; Hatmaker, 2013; Matusovich, et al., 2010; Stevens et al., 2008).

Engineering, meanwhile, can carry inaccurate or incomplete reputations that may influence students' conceptions of engineering careers, and consequently, their sense of career fit. Researchers have highlighted a misalignment between engineering's reputation as a primarily individualistic and computation-heavy occupation compared to an industry reality where engineering roles routinely center upon social elements (Bucciarelli & Kuhn, 1997; Salzman & Lynn, 2010; Trevelyan, 2010; American Society for Engineering Education [ASEE], 2013; Hartmann et al., 2016). Former National Academy of Engineering (NAE) president Charles Vest (2011) describes this mismatch as engineering's " image problem," whereby " engineers [are] perceived to be narrowly focused on technical details, rather than engaged with the social and human dimensions of projects" (p. 9). Baranowski (2011) suggests that an historic under-emphasis on social elements of engineering in engineering school may underlie engineering's difficulty in shedding its "old brand" of technical individualism (p. 14–15). Other literature has similarly critiqued the engineering curriculum as insufficient in its demonstration of the integral social-technical components of engineering work (Bucciarelli & Kuhn, 1997; Trevelyan, 2007, 2010; Sheppard et al., 2009; ASEE, 2013). Further, studies have found that engineering students with stronger self-assessed interpersonal or leadership skills are more likely than their peers to intend to leave engineering after college graduation (Atman et al., 2010; Litchfield & Javernick-Will, 2016). This sorting behavior may relate, in part, to demand-side phenomena, such as higher returns on social skills in other fields of employment (Deming, 2017), but we also call attention to it here given the findings of how students can become exposed to skewed reputations of engineering work during their educational years.

From these past research findings on processes influencing engineering students' career pursuits, we recently constructed and published an aggregate supply-side model of occupational intentions (Magarian & Seering, 2022). This empirically substantiated model explains variance in engineering students' occupational intentions based upon the factors reviewed in this section as well as on students' personal financial situations and work (i.e., internship) histories; notably, variables representing students' universities were statistically insignificant in this aggregate model. In this present study, we incorporate the student-specific factors from among these that appear to intersect with the key dimensions of variation in engineering jobs discussed in the section that follows: anticipates enjoying work involving advanced mathematics, strength of professional identity, anticipates early-career advancement into leadership roles, and satisfaction with creative opportunities in engineering work. Through this study's conjoint survey experiment, we examine interactions between these student-specific characteristics and the job characteristics discussed next to investigate whether (and how) students' awareness of certain realistic engineering job characteristics can influence their occupational preferences.

Key Dimensions of Variation in Engineering Jobs

U.S. public policy designed to strengthen the nation's science and engineering labor supplies has historically centered on boosting student interest broadly across all science and engineering-related fields (Hira, 2010; Teitelbaum, 2014; as examples, see: Augustine et al., 2005; Furman, 2012; President's Council of Advisors on Science & Technology, 2012). Among students in their pre-college years, this "STEM push" has been effective at increasing confidence in relevant academic areas and at raising interest in Science, Technology, Engineering, and Math (STEM) degrees (Valla & Williams, 2012). But this broad campaign has been criticized for conveying vague career concepts (Cannady et al., 2014; Naukkarinen & Bairoh, 2020; Oleson et al., 2014) and has lacked strategies to promote and assess students' career outcomes or satisfaction at later stages (Hira, 2010; Teitelbaum, 2014; Xu, 2013). These programs' success measures have typically rested on counts of STEM degrees awarded and on demographic diversification of degree cohorts, rather than on career outcomes or workforce diversity (Xu, 2013). Yet, the engineering profession has struggled to consistently and equitably convert candidates' adolescent-age interests in the broad field of engineering into specific engineering career outcomes after college (Ayre, et al., 2013; Frehill, 2012; Glass et al., 2013; Main et al., 2021). Further, engineering students with comparatively strong interpersonal skills—a group highly sought by engineering employers (Cappelli, 2015; Salzman & Lynn, 2010)—have been found less likely to take an engineering job at college graduation compared to peers (Atman et al., 2010; Magarian & Seering, 2022).

With certain candidate groups departing engineering pathways to a greater extent than others, and with evidence of substantial variety in engineering work itself, it is unclear which elements of engineering work constitute the most salient influences on students' propensities to remain in the field. In this light, a growing literature has critiqued the generalized lens through which researchers have historically viewed engineering (and STEM) occupations. According to Brunhaver et al. (2013): "many studies fail to address…the varying experiences of early career engineering graduates employed in different engineering sub-occupations" (p. 1). Goold (2012), meanwhile, observed that different engineering roles can include such wide-ranging components as: "process engineering; sales; engineering management; project management; people management; design; risk analysis; pricing; lecturing; research; consultancy; and quality engineering" (p. 322). Other studies further emphasize prior literature's limited discussion on engineering work's variety and on its interdisciplinary nature (e.g., Bucciarelli, 2002; Bucciarelli & Kuhn, 1997; Craps et al., 2021; Stevens et al., 2015; Trevelyan, 2010; Trevelyan & Tilli, 2007), while others, still, call attention to the range of different career progressions that engineers follow (e.g., Allen & Katz, 1995; Pons, 2015; Ranson, 2003; Tremblay et al., 2002).

The literature on engineering work's variety raises the question of whether engineering students are informed of this variety. Labor economists have historically observed that candidates often lack awareness about job possibilities available to them (Autor, 2001; Manning, 2011). According to Autor (2001), "the labor market is replete with imperfect and asymmetric information…workers searching for a job are unlikely to be fully informed about job characteristics" (p. 25), a phenomenon he posited might be ameliorated by the rise of the internet. Later findings, however, suggest that candidates' under-informedness endures due to continued issues with information searchability and comprehensiveness (Manning, 2011). Research has furthermore shown the comprehensiveness of job-related information acquired by candidates to be a factor tied to a subsequent sense of fit at jobs (Saks, 2005; Saks & Ashforth, 1997).

In a jobs landscape as complex and varied as that faced by engineering students, we suspect that students could differ in their informedness about engineering jobs and in their internalized conceptions of engineering work. We proceed to review literature on dimensions of engineering work found to vary or to be commonly misunderstood, including: the use of mathematics in engineering roles, engineers' opportunities for growth into leadership roles, mobility restrictions in engineering positions, and the social components of engineers' work. This literature informs our construction of experimental job manipulations to test hypotheses about the effects that job differences have upon students' attraction to engineering jobs. We introduce these hypotheses in the sections that follow.

The Use of Mathematics in Engineering Roles

Engineering carries a reputation as a mathematics-intensive profession (National Academy of Engineering [NAE], 2008; Winkelman, 2009). Yet, research reveals a sentiment among practitioners that engineering school experiences do not accurately reflect how math is often used in workplaces, with workplace contexts typically involving more support, tools, and collaboration compared to the way students are often required to solve math problems in classes (Alpers, 2010; van der Wal et al., 2017). Moreover, while engineering work certainly rests on principles of mathematics and science, analyses of engineering practice show that individuals' engagement with math varies substantively across different engineering roles (Alpers, 2010; Goold, 2012; Kent & Noss, 2002). Researchers have identified a distinction between specialist roles, requiring advanced expertise and frequent use of math, and generalist roles, requiring a more conceptual-level aptitude and where engagement with math is often limited to working with pre-established software tools and leveraging consultation from specialists (Alpers, 2010; Kent & Noss, 2002; van der Wal et al., 2017).

Engineering specialists whose work centers upon computation and analysis play a distinct part in engineering projects. Such individuals often constitute dedicated expertise groups within larger organizations or are employed in firms that provide an expert service (Alpers, 2010; Kent & Noss, 2002). Kent and Noss describe a "designer-specialist interface" (2002, p. 3) on engineering projects where some individuals necessarily focus on the bigger-picture aspects of projects while others dive into the more rigorous details of supporting analyses. Compared to specialists, studies find that other practitioners use mathematics less frequently (Goold, 2012) and engage in analyses as collaborators, rather than as experts (Alpers, 2010; Anderson et al., 2010). These engineers report using math less intensively in their jobs compared to in engineering school (Alpers, 2010; van der Wal et al., 2017).

Given the marked differences in mathematics use across roles, engineering students' awareness about whether a particular engineering job is that of a computational specialist could be a key factor influencing their attraction to the role. Yet, if uninformed about a role's characterization, students may default to expecting math-intensiveness, given engineering's reputation. We suspect that becoming more informed of a given job's actual mathematics intensiveness may impact different students' attraction to the job in different ways, depending on the students' internalized beliefs about working with math. The prospect of having to work with math has been shown to elicit emotional responses in individuals (i.e., ranging from anticipated anxiety to enjoyment) contingent on factors such as prior academic performance and the development of math self-confidence (Goetz et al., 2008; Sitzman et al., 2010; Goold, 2012). Based on the literature, we hypothesize that engineering students' beliefs about their enjoyment of working with mathematics interact with their informedness about a given engineering job's mathematics intensity to influence their attraction to the job (Hypothesis 1).

Engineers' Opportunities for Growth into Leadership Roles

The engineering profession has historically struggled to consistently describe and publicly promote the advancement opportunities that compose engineering careers. Understanding how individuals' professional identities as engineers endure or adapt during career advancement constitutes a central element of this challenge (Allen & Katz, 1995; Craps et al., 2021; Perlow & Bailyn, 1997; Pons, 2015; Watson & Meiksins, 1991). Literature suggests that notions of engineering and management as separate identities have developed over the past century, inclusive of perceptions that one must depart engineering to enter management, or that one must choose between engineering and management (Biddle & Roberts, 1994; Jemielniak, 2007; Joseph et al., 2012; Perlow & Bailyn, 1997; Trevelyan, 2007). This dialectic view dissociates these realms of work from each other in a manner critiqued as misleading, given engineers' often-integral leadership or managerial duties (Trevelyan, 2007, 2010; Trevelyan & Tilli, 2007) and engineers' common advancement from individual-contributor technical roles into technical management positions (Biddle & Roberts, 1994; Hodgson et al., 2011; Joseph et al., 2012; Mael et al., 2001). Studies suggest that a binary view of the engineering-management distinction masks the existence of myriad role variations, hybridizations, and differences in advancement paths among engineers (Watson & Meiksins, 1991; Allen & Katz, 1995; Trevelyan, 2007; Paton & Hodgson, 2016).

Prior studies identify at least three means by which leadership or managerial job components tend to manifest in engineering careers. First, engineers can make distinct jumps from individual-contributor engineering roles into management positions. These transitions have been shown to lead to both people management positions as well as to project or product management positions (Biddle & Roberts, 1994; Mael et al., 2001; Carbone & Gholston, 2004; Ebert, 2007; Hogdson et al., 2011; Joseph et al., 2012). Secondly, engineers' positions can evolve into technical-managerial hybrid roles centered on project coordination in individuals' technical areas of expertise (Allen & Katz, 1995; Paton & Hodgson, 2016; Petroni, 1999). In such cases, as Paton and Hodgson (2016) explain, "[practitioners see] project management as fundamentally an extension of a technical (engineering) role, which prioritises extensive knowledge of the product and technology" (p. 36). Lastly, a growing literature calls attention to leadership elements intrinsic to engineering practice itself, including among early-career roles. These studies note that non-manager engineers must frequently coordinate the work of others, lead small groups, and leverage social skills in order to contribute effectively on engineering projects (Kumar & Hsiao, 2007; Trevelyan, 2007, 2010; Rottman et al., 2015; Hartmann et al., 2016). Literature suggests that leadership, coordinative, and managerial aspects of engineering work and careers have historically been under-examined relative to their prevalence in practice (Trevelyan, 2007, 2010).

Among studies examining engineers' transitions into management, a subset describes transitions to project or product management roles (e.g., Carbone & Gholston, 2004; Ebert, 2007; Hodgson et al., 2011; Nicholas & Steyn, 2017). Project management roles involve developing and managing schedules and budgets, mitigating risks, and allocating resources based on priorities (DiVincenzo, 2006; Heagney, 2016). Product management roles, meanwhile, center on discerning customer needs, defining product requirements, and creating product development plans (Ebert, 2007; Gorchels, 2012). Both roles involve elements of leadership, such as establishing shared goals, clarifying work scope, and guiding teams to perform toward these aims (DiVincenzo, 2006; Gorchels, 2012). Gnanasambandam et al. (2017) estimate that engineering firms typically operate with ratios of one project manager per every 4 to 5 contributing engineers or one product manager per 8 to 12 engineers. The majorities of these management roles are filled by individuals with technical backgrounds (Carbone & Gholston, 2004; Ebert, 2007). Further, many firms sponsor employee development programs to help engineers transition to these roles (Carbone & Gholston, 2004; Hodgson et al., 2011; Nicholas & Steyn, 2017). Yet, despite these clear pathways from engineering into project or product management, existing studies do not reveal how consistently aware engineering students are of such trajectories, nor whether students consider them to fall within or outside of their concept of an engineering career.

More broadly, we question the extent to which engineering students are informed about the variety of leadership and management opportunities that stem from careers in engineering, including at early-career stages. If students are uninformed about these aspects of engineering work, we suspect, based on engineering's general reputation described in the literature, that they will tend toward under-estimating the opportunities to attain leadership or management roles from entry-level positions. We further suspect that becoming informed of such opportunities will have different effects upon different subsets of engineering students; specifically, that those with a higher self-appraised leadership ability will be more attracted to a given job upon learning of its leadership opportunities compared to their peers. We hypothesize that students'self-appraisal of their ability to fulfill leadership roles interacts with their informedness about a given engineering job's leadership growth opportunities to influence their attraction to the job (Hypothesis 2).

Mobility Restrictions at Engineering Positions

Employers' restriction of engineers' career mobility has received considerable attention in both scholarly literature and in the popular press in recent years (for reviews, see: Lobel, 2013; Hyde, 2015). This attention has centered on employers' efforts to protect intellectual property and preserve investments in employee development, including, for instance, non-compete covenants restricting near-term employment at competing firms (Cappelli & Keller, 2014; Lester, 2001; Marx, 2011) and training repayment agreements that establish job commitment expectations (Lester, 2001; Long, 2005; VonBergen & Mawer, 2007; Cappelli & Keller, 2014). Marx (2011) found that nearly half of U.S. "technical professionals" have been asked to sign a restrictive covenant of some form. Some individuals, however, have successfully challenged the legality of restrictive covenants in courts (Lester, 2001; Long, 2005), and some U.S. states have enacted prohibitive legislation against them (Marx et al., 2015). Legality notwithstanding, employer-designed restrictive policies have occupied a sizable place in the discourse on engineering work, including press coverage that may contribute to public perception of immobility associated with engineering careers (Lobel, 2013).

Among the comparably less severe of these restrictions are training repayment agreements tied to commitment expectations (Long, 2005; VonBergen & Mawer, 2007). When in place, these agreements specify a term of employment, usually between 1 and 3 years, during which an employee agrees to remain with an employer, lest they owe the employer repayment of a portion of funds contributed toward training and development upon early departure (Lester, 2001; Long, 2005; VonBergen & Mawer, 2007; Cappelli & Keller, 2014).

The literature on mobility restriction inspires the question of whether students' perceptions about commitment expectations influences their attraction to engineering jobs.

Research suggests that many engineering students' professional identities are still nascent at the time they prepare to graduate (Lichtenstein et al., 2009; Stevens et al., 2008). Awareness of a given job's commitment expectations may therefore shape job attraction differently depending on students' strength of professional identity and the degree of alignment between identity and job. For instance, engineering students possessing a strong professional identity in a given field could be comparably less deterred by commitment expectations at jobs in that field, especially if employers will be supporting professional development in their areas of interest. In this light, Benson et al. (2004) found that firms' investment in skill development in employees' specialty areas can be motivating and can encourage retention. Conversely, we expect that a job's imposition of a commitment expectation could reduce job attraction among those who are uncertain about their professional identity and developmental interests. We hypothesize that engineering students' strength of professional identity interacts with their informedness about a given engineering job's commitment expectations to influence their attraction to the job (Hypothesis 3).

The literature on employers' mobility-restrictive policies has also examined how the presence of creative work can shape individuals' reactions to restrictive policies. Amir and Lobel (2013) found that individuals' aversion to mobility-restrictive policies is reduced in cases where they perceive jobs' work as creative rather than rote. Studies also indicate that students' attraction to the engineering profession is higher when they perceive engineering to involve creativity (Atwood & Pretz, 2016; Bernold et al., 2007). This literature again suggests that different student subsets' attraction to a given job will be affected differently by knowledge of commitment expectations at the job. We hypothesize that engineering students' satisfaction with creative opportunities in engineering work interacts with their informedness about a given engineering job's commitment expectations to influence their attraction to the job (Hypothesis 4).

Social Components of Engineering Work

Numerous studies have examined the social characteristics of engineering roles in industry. Beginning in the late twentieth century, researchers began to contest engineering work's reputation as predominately rooted in individualistic problem solving, demonstrating, instead, that engineering work is often highly interactive (e.g., Bucciarelli, 2002; Bucciarelli & Kuhn, 1997; Perlow & Bailyn, 1997; Robinson, 2012; Stevens et al., 2015; Trevelyan, 2007, 2010). Trevelyan (2010), for instance, observed that engineers typically spend more than half of their time interacting with others, concluding that "human performance and social interactions lie at the core [of engineering practice]" (p. 190). Yet, literature also highlights differences in the social components of engineering work across different role types. Studies discuss at least three types of individual contributor engineering roles across which social interaction manifests differently: technical specialist roles marked by comparably large portions of time spent on individualistic work, team-based collaborative roles characterized by frequent interaction, and inter-organizational coordinative roles marked by substantial time spent coordinating technical work across functional or organizational boundaries.

A subset of this literature examines the roles that are comparatively individualistic (Alpers, 2010; Anderson et al., 2010; Kent & Noss, 2002). Anderson et al. (2010), for example, describe roles consisting substantially of working alone to run computer simulations, or to design components using Computer-Aided Design (CAD) programs, or to review designs to ensure they meet standards, among other activities (p. 161).

Meanwhile, certain computational specialist roles, as described earlier in *The use of mathematics in engineering roles*, have also been shown to be substantially individualistic (Alpers, 2010; Kent & Noss, 2002), but, as Anderson et al. (2010) make clear, individualistic roles at engineering firms are not limited to math-heavy roles.

Several other studies, meanwhile, emphasize the prevalence of team-based collaborative roles in engineering (Bucciarelli, 2002; Bucciarelli & Kuhn, 1997; Robinson, 2012; Stevens et al., 2015; Trevelyan, 2010). Robinson (2012), for instance, found peer collaboration to be integral to many engineers' routines, and Bucciarelli (2002) observed: "engineering design is the business of a collective or team" (p. 219). Trevelyan (2007), however, draws a distinction between general forms of "teamwork" frequently referred to in descriptions of engineering practice and an additional context of engineering work that centers on technical coordination across functional or organizational boundaries. As Trevelyan explains, "working in teams is a different experience [than extra-team coordination]. Most of the coordination reported in [Trevelyan's study] occurred outside the context of a particular team" (p. 198). Trevelyan characterizes this type of coordination as entailing elements of: influencing members of other functions to perform needed tasks, monitoring and supervising the work of contractors, engaging with external agencies, and interfacing with clients (p. 197). Several other studies provide similar examples of coordinative roles in engineering practice (e.g., Herbsleb, 2007; Lakemond et al., 2006; Stevens et al., 2015; Twigg, 1998).

Beyond describing variety in social characterizations of engineering roles, literature has documented trends of gendered sorting of individuals into role types. Past studies have observed a greater tendency of women engineers to undertake roles with comparably prevalent social and coordinative components, while men were found more likely to undertake individualistic technical roles (Cech, 2013; Seron et al., 2016, 2018). Researchers describe this phenomenon as "intra-professional gender segregation" (Cech, 2013), and have explored how such trends are reproduced over time through professional socialization experienced by students in pre-professional settings (Seron et al., 2016, 2018). Findings suggest that these socialization processes can influence gendered notions of role fit and confidence, such as through initiation routines on project teams entailing competitive establishment of technical "pecking orders" among teammates, interchanges that can undermine the formation of confidence (Seron et al., 2016). This literature suggests that socialization processes can influence women's tendencies toward the more social, coordinative, and administrative roles on engineering teams.

Yet, given the literature's descriptions of nuanced variation in the social components of different engineering roles, we again question the extent of engineering students' awareness of role variation and availability. We expect, given engineering's enduring reputation as individualistically technical, that students who are uninformed about a given engineering role's social aspects will tend to perceive the role as more individualistic than it actually is. Further, given the evidence of gendered preference trends, we anticipate that when students become informed of an engineering role's social components, women's and men's attraction to the role may be impacted differently, on average, with women reacting comparatively more positively than men to information about a role's social or coordinative components. We therefore hypothesize that gender interacts with informedness about a given engineering job's social components to influence students' attraction to the job (Hypothesis 5).

Summary

Based on the literature reviewed, we proceed under the assumption that engineering students likely hold inconsistent and incomplete conceptions of engineering work. We base this assumption on the documented variation in engineering work itself, known gaps between engineering educational experiences and aspects of workplace practice, and imperfections of information flow in labor markets. We next outline experimental methods to test our hypotheses (Table 1) on the effects of job attribute informedness upon engineering students' attraction to jobs. The job differences we tested correspond with the variations in engineering work reviewed from the literature: differences in mathematics content, leadership growth opportunities, commitment expectations, and social characteristics of engineering jobs. We do not claim that these variations are the only ones present across engineering practice; rather, we focus on them due to their notable coverage in the literature, and assumingly, a corresponding prevalence in practice. We next outline our conceptualization and operationalization of experimental job attribute manipulations in the *Methods* section that follows.

Methods

Research Setting

We conducted this study' conjoint survey experiment at nine U.S. universities, asking participants, all of whom were mechanical engineering seniors from the class of 2017, to provide information about themselves and their career plans and to rate six different engineering job profiles. Each profile's content was randomized across four job attributes. Randomized profiles were presented in side-by-side pairs in accordance with methods presented by Hainmueller et al. (2014). This scheme asked respondents to indicate a preference toward one of the two from each pair, as well as to assign an appeal scale rating to both job profiles in the pair. This approach simplifies participants' decision tasks while acquiring redundant measurements to enable robustness checks of results (Hainmueller et al., 2014). The survey experiment took place in classroom settings and employed a paper-based survey form to maximize response rates by integrating the survey task into participants' typical class time.

We sampled all participants from a single academic major and graduation year to control for (and minimize) participants' exposure to transient job market factors that might influence their overall interest in working at an engineering job. Research has shown engineering students' career interests to be significantly associated with market conditions (Bardhan et al., 2013; Lynn et al., 2018; Ryoo & Rosen, 2004). A participant sample composed of varied majors or graduation years could therefore contain inherent differences in attraction to engineering work. We chose to sample mechanical engineering majors given that field's job market stability: the U.S. Bureau of Labor Statistics assessed mechanical engineering jobs' growth as " average" relative to growth rates across all occupations near the time of our survey (U.S. Bureau of Labor Statistics [BLS], 2018a). By contrast, engineering job markets in computer software-related areas were experiencing sharp growth (BLS, 2018b). We know of no theoretical reasons why this experiment's examination of job preferences based on mathematics demands, leadership opportunities, commitment expectations, and social characteristics would not generalize across the broader population of engineering students. However, follow-on research is required to verify transdisciplinary generalization, as we discuss in *Limitations of results and considerations for future work*.

We took steps to minimize participant self-selection biases in the sample, as students' choice to participate in a study on job preferences could result in disproportionate representation (or exclusion) of attitudes about working in their field of study. The mechanical engineering curriculum provides a unique opportunity to reach entire senior year cohorts at occasions of required attendance: senior capstone design course sessions. We designed the survey experiment to be administered at these sessions. Through partnering negotiations with department chairs and capstone instructors across the nine schools, we reconciled schools' varied constraints to arrive at a survey designed to take 12 minutes to complete (see: *Development of a survey instrument with embedded conjoint experiment*), either at the beginning or end of a scheduled class. At each session in which the survey was conducted, instructors announced that a voluntary survey about engineering careers would be part of the day's class. On-site research personnel then distributed and collected the survey forms at these sessions. This short-duration, in-class approach resulted in a near-90% participation rate and garnered over 1000 survey responses.

We targeted a diverse range of university types from which to draw survey participants, including large and small engineering schools at public and private institutions spanning a broad geographical dispersion. We recruited these partner universities through an email campaign to department chairs and capstone course instructors at various accredited mechanical engineering programs. The campaign resulted in agreements to conduct the survey at Boston University, Carnegie Mellon University, Massachusetts Institute of Technology, Penn State University, Santa Clara University, Texas A&M University, Tufts University, the University of Connecticut, and the University of Michigan. This mix includes four public and five private institutions from six U.S. states. As part of our partnering agreements with the universities, we agreed not to publish research findings in a manner that conveyed direct university-to-university comparisons.

Development of a Survey Instrument with Embedded Conjoint Experiment

This study's survey contained questions associated with participant-specific independent variables, questions constituting the embedded conjoint experiment, and questions composing the post-experiment manipulation checks. The first and last pages of the 5-page survey form were identical for all participants and were dedicated to the collection of participant-specific data and manipulation checks. The middle three pages contained experiment content that was randomized across participants. Each survey form was marked with a unique identification number.

The survey acquired participant-specific independent variables in three areas: variables theoretically pertinent to engineering students' career intentions, demographic variables, and additional variables for purposes of empirical control. The full set of survey questions for all independent variables is presented in Table 6 in this paper's appendix. Here we leveraged survey questions from a recent empirically substantiated supply-side model of engineering students' occupational pursuits (Magarian & Seering, 2022) for those independent variables theoretically linked with career intentions: anticipates enjoying work involving advanced mathematics, strength of professional identity, anticipates early-career advancement into leadership roles, and satisfaction with creative opportunities in engineering work. As shown in Appendix Table 6, we also collected participant-specific data on occupational plans, expected salary, gender and race demographics, graduation date, and undergraduate major.

The survey pages dedicated to the conjoint experiment followed the layout developed by Hainmueller et al. (2014) and shown in Fig. 1, inclusive of pairs of randomized job profiles with rating questions. By convention, each pair of profiles is referred to as one experimental "round." Conjoint methods allow participants to rate multiple rounds of profiles which contribute to a study's overall observation count. Standard errors of job preference measurements are then clustered by participant to account for the origination of multiple measurements from the same individual (Hainmueller et al., 2014). We elected to include three rounds (i.e., six total profiles for respondents to rate) in consideration of our 12-min target completion time and based upon pilot testing of the survey with student volunteers.

Below you will see several pairs of job descriptions.

Please read each pair, compare the two jobs, and answer the questions that follow each pair. As you answer, **assume** that each job is located somewhere desirable to you and that the product(s) the company makes are of interest to you.

	Job A		**Job B**
	Mechanical Design Engineer		**Mechanical Design Engineer**
Salary	$78,950 /year	**Salary**	$78,990 /year
About the Company	19 year-old company, 500 employees	**About the Company**	20 year-old company, 400 employees
Credentials	B.S. in Mechanical Engineering required Strong skills required in differential equations and mechanical analysis (e.g., fluids, thermal, structural, dynamics)	**Credentials**	B.S. in Mechanical Engineering required
Responsibilities	You'll work on a design team in new product development. You'll develop concepts, collaborate on design details, choose components and materials, and verify the design through modeling and test. We are seeking an expert comfortable with computation and analysis (both hand calculations and FEA), given the tight margins for error in this product. You'll spend most of your time working on your own tasks, while a small portion of your time will involve collaborating with peers.	**Responsibilities**	You'll work on a design team in new product development. You'll develop concepts, collaborate on design details, choose components and materials, and verify the design through modeling and test. You'll work alongside an engineering analysis group that will run any detailed computation necessary to support your design work. You'll spend most of your time in collaborative team environments, communicating and coordinating about designs.
Other	This highly selective opportunity is with the company's Advanced Projects Division, where a minimum of a 3-year commitment to remain with the company is expected due to the specialized and proprietary skills set you'll develop.	**Other**	This position includes a leadership "fast track" option for those interested in transitioning into product or project management (PM) roles. Qualified candidates can achieve PM roles within 1-2 years, if desired. A salary increase accompanies advancement.
Benefits	Generous year-end bonus, Best-in-class healthcare, 401(k), free gym membership, flexible hours.	**Benefits**	Generous year-end bonus, Best-in-class healthcare, 401(k), free gym membership, flexible hours.

If you had to choose to work at one of these two jobs, which would you select?

☐ Job A ☐ Job B

Based on the limited information in the job descriptions, please indicate the **potential appeal** of each of the jobs to you:

1	2	3	4	5	6	7	1	2	3	4	5	6	7
Little/no potential appeal			unsure			Potentially very appealing	Little/no potential appeal			unsure			Potentially very appealing

Fig. 1 Example layout of a single conjoint survey experiment round (job profile pair)

Post-experiment manipulation checks on the last page of the survey form allowed us to verify that job preferences measured in the conjoint experiment were non-spurious and could be attributed to respondents' reactions to the manipulated information in the job profiles. These manipulation checks are described later in *Data collection, verification, and analysis*.

Conceptualization and Operationalization of Job Attribute Manipulations

We developed the set of variable job attributes employed in the experiment's job profiles based on the literature review (see: *Key dimensions of variation in engineering jobs*) and as shown in Table 2. Our experiment tested the effects of four job profile manipulations, each imparting randomized differences within one or more of the job profile information categories shown in Fig. 1: "credentials," "responsibilities," or "other." We refer to the variants of a particular manipulated job attribute as the "states" of that attribute; therefore, manipulations entailed presenting different attribute states to participants in a randomized manner.

Beyond the manipulated elements of job profiles, other elements were held consistent across all profiles. These consistent elements are listed in Table 3. All profiles, for instance, had an identical job title, "Mechanical Design Engineer," all listed an identical set of "benefits," and all contained identical introductory language within the "responsibilities" category. Meanwhile, "salary" and "about the company" were also designed to be consistent job elements, but we imparted miniscule variations in this information across job profiles (as shown in Table 3) to heighten participants' sense that each profile was unique and needed to be read fully. For example, the posted salary was varied by ± $50 around a mean of $78,940. The small variations in salary and company information were intended to be meaningless to participants, a notion that we empirically confirm as part of the experiment's results verification. Further, instructions advised participants to "assume each job is located somewhere that is desirable to you, and that the product(s) the company makes are of interest to you."

The job profile information not involved in the manipulations was designed to make profiles appear neutral or modestly attractive so that participants' focus would be on the manipulated differences. The salary, for example, was set to be slightly higher than the anticipated average salary offered to an entry-level mechanical engineer so that salary concerns would not be at the forefront of participants' minds—but not so high as to be startling. The elevated salary was 10–15% above reported U.S. average starting salaries of mechanical engineers, depending on location (Glassdoor, 2016). Meanwhile, company size and age were set so that the company would neither appear to be a young start-up, nor an old, large company.

We conceptualized the manipulation of jobs' math intensity as a difference between roles involving non-intensive mathematics in a supportive environment and roles involving intensive math requiring advanced abilities. We operationalized this manipulation through the two contrasting attribute states shown in the first row of Table 2. In the case of the non-intensive math attribute state, no mention is made of requisite credentials in math beyond an engineering bachelor's degree, while job responsibilities include "[working] alongside an engineering analysis group that will run any detailed computation necessary to support your design work." This language reflects the realistic scenario of a designer-specialist interface (Kent & Noss, 2002) and suggests that this role is one of a generalist design engineer. In contrast, the math-intensive attribute state suggests a specialist role, emphasizing individual math ability and illustrating the analytical nature of the role.

Table 2 Summary of experimental job profile manipulations

Job attribute	Job profile content differences across attribute states		
	State 0	State 1	State 2
Mathematics intensity	Non-intensive with support emphasized Credentials: "B.S. in Mechanical Engineering required" Responsibilities: "You'll work alongside an engineering analysis group that will run any detailed computation necessary to support your design work"	Intensive with individual ability emphasized Credentials: "B.S. in Mechanical Engineering required" Strong skills required in differential equations and mechanical analysis (e.g., fluids, thermal, structural, dynamics)" Responsibilities: "We are seeking an expert comfortable with computation and analysis (both hand calculations and FEA), given the tight margins for error in this product."	N/A
Leadership growth opportunity	No opportunity discussed Other: N/A	Opportunity discussed Other: "This position includes a leadership 'fast track' option for those interested in transitioning into product or project management (PM) roles. Qualified candidates can achieve PM roles within 1–2 years, if desired. A salary increase accompanies advancement."	N/A
Commitment duration expectation	No duration discussed Other: N/A	Duration and skill development discussed Other: "This highly selective opportunity is with the company's Advanced Projects Division, where a minimum 3-year commitment to remain with the company is expected due to the specialized and proprietary skills set you'll develop"	N/A

Table 2 (continued)

Job attribute	Job profile content differences across attribute states		
	State 0	State 1	State 2
Social characterization of work	Individualistic role	Collaborative team-based role	Inter-organization coordinative role
	Responsibilities: “You’ll spend most of your time working on your own tasks, while a small portion of your time will involve collaborating with peers”	Responsibilities: “You’ll spend most of your time in collaborative team environments, communicating and coordinating about designs”	Responsibilities: “You’ll spend most of your time interacting with vendors, interpreting specifications, and/or updating design details on drawings. As designs are completed, you’ ll have on-call responsibility to help keep production running smoothly”

Table 3 Job attributes not subject to experimental manipulation

Job attribute	Content
Job title	"Mechanical design engineer"
Salary	$78,940 (± $50)
About the company	Company age: 20 years (± 1 year) Company size: 450 employees (± 50 employees
Responsibilities	"You'll work on a design team in new product development. You'll develop concepts, collaborate on design details, choose components and materials, and verify the design through modeling and test"
Benefits	"Generous year-end bonus, best-in-class healthcare, 401(k), free gym membership, flexible hours"

The leadership growth opportunity manipulation was conceptualized in a binary manner: a job profile either would or would not convey a path to a future leadership role. We operationalized this manipulation through a difference between attribute states' content within the "other" profile category (per the second row of Table 2). As follows from our literature review, the opportunities for advancement into project or product management roles composing this manipulation constitute realistic career trajectories for engineering graduates. Meanwhile, the job manipulation conveys that the advancement opportunity is neither guaranteed nor required. A timeline for realization of the opportunity, "1–2 years," is provided, as is an acknowledgement that increased compensation accompanies advancement. These latter features provide specific and pragmatic details of the opportunity.

Our manipulation of jobs' expected commitment duration reflects a divide in how engineering employers approach investing in employee development: some enact explicit policies to retain those in whom they invest in specialized skills development, while others do not (Marx, 2011). The manipulation (shown in the third row of Table 2) therefore includes one attribute state with no mention of a commitment duration, and another that outlines terms of commitment expectations linked with specialized employee training and development. According to the literature, policies that tie commitment expectations to specialized skills development have a greater precedent for legal legitimacy (Lester, 2001). In the attribute state that contains a commitment expectation, the job profile emphasizes the role's positioning within the company's "Advanced Projects Division" and states that "a minimum 3-year commitment to remain with the company is expected due to the specialized and proprietary skills set you'll develop."

Finally, we conceptualized a three-state manipulation pertaining to the social characteristics of jobs that follow from our literature review. We operationalized this manipulation through varying text within the "responsibilities" category of the job profile, as shown in the last row of Table 2. The first attribute state emphasizes an individualistic environment (e.g., "you' ll spend most of your time working on your own tasks"), the second state focuses on teamwork (e.g., "you' ll spend most of your time in collaborative team environments"), and the third state emphasizes inter-organization coordination (e.g., " you' ll spend most of your time interacting with vendors").

Data Collection, Verification, and Analysis

Data entry from paper survey forms collected at the nine universities was conducted by the first author and was independently repeated by a research assistant to ensure accuracy. The dataset was then loaded into the statistics program Stata v.15. After compiling summary statistics, the primary analysis performed on the data entailed computing Average Marginal Component Effects (AMCEs) for each manipulated job attribute. Here, an AMCE represents the average difference in probability of a job being preferred between two different states of a particular job attribute, with this average taken over all combinations of the remaining manipulated job attributes. For instance, the AMCE for the mathematics intensity attribute represents the average difference in probability of participants preferring the math-intense job variant compared to the math non-intense job variant, with all other job attributes assumed to exist in random combinations across these math-intense and non-intense states. This analytical approach allowed us to quantify the effect that each unique attribute manipulation had upon participants' expressed job preference.

As Hainmueller et al. (2014) demonstrate, AMCEs are identified non-parametrically by linear regression of the outcome variable (in this case, job preference) upon sets of indicator variables representing the manipulated attributes, provided that the attributes are independently randomized and the ordering of job profile evaluation tasks does not influence respondents' preference ratings. We computed AMCEs (and their confidence intervals) using Hainmueller et al.'s methods, including verification tests.

As an initial verification test, we confirmed that attribute manipulations' effects were independent of job profiles' physical positions within the survey form. This test involved verifying that regression coefficients for attribute state variables were not statistically different when the outcome variable was regressed upon the attribute state variables alone, compared to when the outcome variable was regressed upon the attribute state variables, indicator variables for job profile page positions, and the full set of interaction terms between the page position and attribute variables.

We then conducted a robustness check (Hainmueller & Hopkins, 2015) to establish that full-sample AMCEs are similar when computed in two different ways: from the survey experiment's forced-choice measure of the outcome variable (i.e., binary job preference), and, secondly, from the appeal scale measure of the outcome variable (dichotomized from a 7-point scale to a binary format). This check provides confidence that the forced choice construction of the job preference measure did not skew participants' expression of job appeal relative to its measurement on an unconstrained scale.

We next conducted a realism check on the design of our job profiles. Since all profiles represent engineering jobs, we expected that those participants who planned to work as engineers after graduation would, on average, rate profiles higher than other participants. We therefore tested for the significance of the difference in mean job appeal responses between these two groups. Higher average appeal ratings from those pursuing engineering jobs would give confidence that the overall set of job attributes conveyed realistic representations of the profession. Though we expected some attribute combinations would appeal to participants not pursuing engineering, we deemed it important that the broad set of job profiles not carry an elevated average appeal that diverged excessively from participants' general notions of engineering work. Similarly, in another test of realism, we computed the full-sample mean job appeal ratings for each of all 24 possible combinations of job attributes in the experiment. Here we sought to confirm that no particular job profiles were universally unappealing to participants. For instance, verifying that even the least popular among job configurations was appealing to a substantive subset of participants would suggest realism; by contrast, a universally unappealing job would suggest an unreasonable configuration. While these tests do not carry absolute meaning, they allowed us to qualitatively assess the reasonableness of the job profiles.

Finally, we conducted manipulation checks to verify that participants recognized the job profile differences intended by the randomized manipulations. Following the three rounds of job profile rating tasks in the survey form, we presented participants with a series of manipulation measures as shown in Table 7 in this paper's appendix. The measures' heading reads, "Place a check next to any/all of the attributes that differed meaningfully among the different jobs," and was followed by a list of eight attribute options, four of which were intentionally manipulated in the experiment, and four of which were not. We then ran statistical tests to confirm that correct and false-positive responses differed significantly, both overall, as well as for each of the four intentionally manipulated attributes separately.

The procedures outlined above allowed us to establish and verify a baseline characterization of job preferences for the full participant sample. After establishing this baseline, we proceeded to explore the hypothesized interactions listed in Table 1. We present this study's findings in the section that follows, beginning with summary and descriptive statistics for the participant sample. We then present the AMCEs for job attribute manipulations at the full sample level, followed by evaluations of the individual hypothesized job preference interaction effects. Finally, we present a multivariate model of job preference that incorporates both the full set of job attribute manipulations and the full set of hypothesized student characteristic-job attribute interactions.

Results

Description of Sample

Conducting the survey at the nine host universities resulted in a sample of 1,061 participants. The average institution-specific participation rate among target respondents was 86.9%; this rate ranged from 81.9% to 92.0% across the universities. Table 4 presents summary statistics for the sample, beginning with statistics for the four key independent variables discussed in *Supply-side processes and occupational intentions of engineering students*. As shown, small majorities among participants indicated that they anticipated enjoying work involving advanced mathematics (55.9%) and identified with a specific profession (54.8%). Half of the candidates anticipated early-career advancement into a leadership role (50.0%) and expressed satisfaction with creative opportunities in engineering work (49.9%). Table 4 also presents information on participants' career intentions, demographics, institution type, and graduation date. All participants expected to complete their undergraduate degrees in the year 2017 (an inclusion criterion for this study).

Of all participants who submitted a survey form, 1,054 (99.3%) contributed responses to the job profile assessment questions that composed the survey's embedded experiment. Among those who participated in the experiment, 98.4% completed all three rounds of experimental job profile ratings, resulting in a total of 6,220 job preference observations from 1,054 unique individuals.

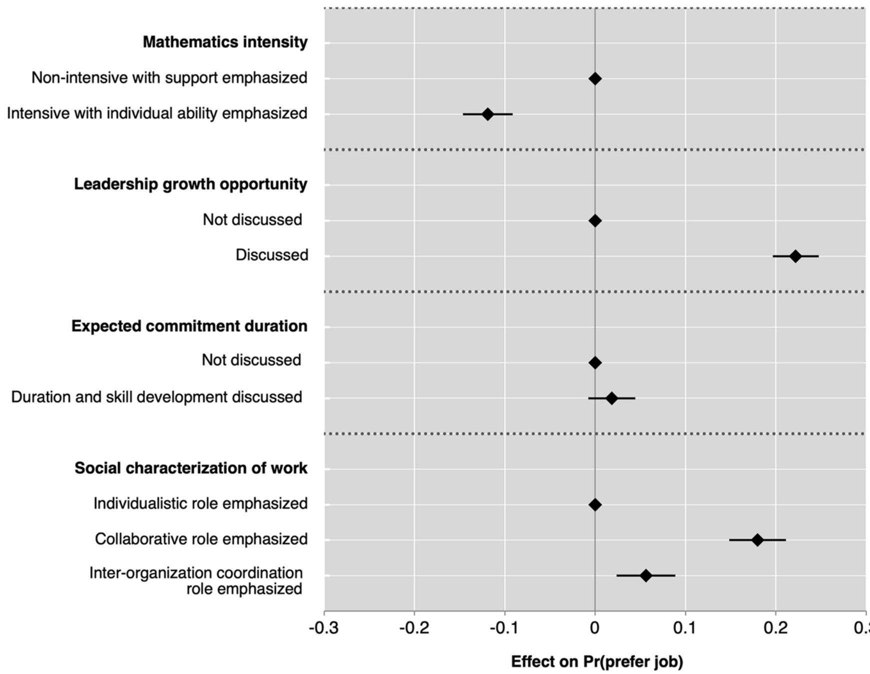
Table 4 Summary and descriptive statistics on survey participant sample

	Mean	(SD)	Number of observa-tions	Percentage
Key participant-specific independent variables (supply-side factors)				
Anticipates enjoying work involving advanced mathematics			593	55.9
Strong professional identity (identifies with a specific profession)			581	54.8
Anticipates early-career advancement into leadership role (by age 25)				
7-pt scale assessment	4.61	(1.37)		
Participant rates self above scale midpoint			531	50.0
Satisfied with creative opportunities in engineering work				
7-pt scale assessment	4.47	(1.29)		
Participant rates self above scale midpoint			529	49.9
Participant career plans				
Expected first full-time job				
Engineering[a]			748	70.5
Non-engineering			255	24.0
Salary expectation at first full-time job	$70,142	($13,740)		
Expects to attend graduate school directly after college[b]			230	21.7
Expects to serve in the military direclty after college[c]			19	1.8
Participant demographics				
Female			245	23.1
White			752	70.9
Asian			205	19.3
Hispanic or Latino/Latina			87	8.2
Black or African American			40	3.8
All other			24	2.3
Other participant information				
Institution type				
Public university			624	58.8
Private university			437	41.2
Graduation term				
Spring 2017			965	91.0
Summer 2017			21	2.0
Fall 2017			75	7.1
Total participants in sample:			1061	

[a]Students self-identified their expected first full-time job as being in " engineering" or in another field. See Table A1 in the Appendix for survey question

[b]Those who indicated that they expected to attend graduate school directly after college are also counted in the "engineering" and "non-engineering" occupational categories above based on their expected occupation immediately following graduate school

[c]Those who indicated military service as their first full-time job are not counted in the "engineer" or "non-engineer" occupation categories above



Notes:
This plot shows estimates of the Average Marginal Component Effects (AMCEs) of randomly manipulated job attributes on the probability of a job being preferred. Horizontal bars represent 95% confidence intervals. The points without horizontal bars denote the reference state for each attribute. The plot is based on the study's full sample, consisting of 6,220 observations from 1,054 unique participants.

Fig. 2 Job attribute manipulations' effects upon probability of job preference (full sample)

Effects of Manipulating Job Attributes on Job Preferences

Figure 2 shows AMCEs computed for each of the experiment's job attribute manipulations based upon all job preference observations collected. Point estimates of the AMCEs are indicated by dots in Fig. 2, while horizontal bars show each estimate's 95% confidence interval. The horizontal axis is demarked to indicate manipulations' effects upon the probability of a student preferring a given job configuration over the other possible job configurations. For each job attribute, one of its states is designated as a reference state, as is indicated by a dot without confidence interval bars located on the zero-intercept line of the horizontal axis. Manipulations' effects on probability of job preference are therefore shown as the horizontal difference between an attribute state's AMCE point estimate and its reference. For example, in the case of mathematics intensity, the AMCE point estimate for " intensive with individual ability emphasized," compared to the reference state of " non-intensive with support emphasized," indicates a − 0.12 effect on estimated preference probability, meaning that we expect the likelihood that students will prefer any given job decreases by 12%, on average, if the job is mathematically "intensive" compared to "non-intensive."

The set of AMCEs shown in Fig. 2 was estimated by regression of the job preference dependent variable upon a set of dichotomous indicator variables for attribute states (with standard errors clustered by participant). Four statistically significant manipulations at the full-sample level were identified in this analysis: manipulation of mathematics intensity from “ non-intensive” to “intensive” had a significant negative effect on probability of job preference ($p<0.001$); manipulation of leadership growth opportunity from “ not discussed” to “discussed” had a significant positive effect on probability of job preference ($p<0.001$); manipulation of social characterization of work from “ individualistic” to collaborative” had a significant positive effect on probability of job preference ($p<0.001$); and, manipulation of social characterization of work from “individualistic” to “inter-organization coordination” had a significant positive effect on probability of job preference ($p<0.01$). Given that these significant effects were observed at the full-sample level, they suggest general preference trends among the study participants.

As described earlier in *Data collection, verification, and analysis*, we next conducted a series of verification checks on the observed attribute manipulation effects. We began by assessing the independence of manipulations’ effects from job profiles’ physical positions within the survey form by evaluating the statistical similarity of coefficients computed in two ways: first, by regressing the dependent variable on the set of attribute state indicator variables (e.g., our baseline model), and, second, by regressing the dependent variable upon the attribute state indicators variables along with indicator variables for job profile page positions and with the full set of interaction terms between the page position and attribute state indicator variables. Including these interaction terms in the regression allowed us to detect whether there were any undesirable interactions between job profile page positions and attribute states influencing the dependent variable. We then employed Stata’s *suest* post-estimation command to test the null hypothesis that the attribute state indicator variables’ coefficients were equivalent when computed in these two different ways. We could not reject this null hypothesis for any of the coefficient equivalency tests ($0.16<p<0.66$ among tests). This statistically non-significant finding supports the notion that job attribute manipulation effects on job preference are not significantly associated with job profile positions. The result also supports the notion that the non-experimental job profile parameters listed in Table 3 (i.e., information on “salary” and “about the company”) do not have a significant effect on job preference, since these parameters were varied consistently by job profile position.

We next assessed the sensitivity of the job preference findings to differences between forced choice and appeal scale measurement approaches. The forced choice measure (i.e., preferred job selection) is the basis for the dependent variable reported throughout this paper. To carry out this robustness check in accord with methods from Hainmueller and Hopkins (2015), we first dichotomized the appeal scale data by coding all responses above the scale midpoint as “1” and all remaining responses as “0”. We then ran the same regression analysis used to generate Fig. 2, above, except with the dichotomized appeal scale variable as the dependent variable, resulting in a set of AMCEs similar to those shown Fig. 2. We report these results in Fig. 9 in this paper’s appendix. Because the substantive meanings of the forced-choice job preference measurements and the appeal scale measurements are not identical, the results cannot be formally compared. However, as Hainmueller and Hopkins (2015) suggest, robust results should convey the same general preference behaviors across the two measurement methods. Here, we observe that the same attribute manipulations that are shown to be statistically significant in Fig. 2 are also significant in Fig. 9, each with similar magnitudes. These findings suggest that the forced choice measures do not unrealistically constrain participants’ ability to express job preference.

Following the robustness test of the job preference measure, we next conducted realism checks for the job attribute manipulations. We expected mean dichotomized job appeal ratings from participants intending to work as engineers to be higher than those of other participants. Our findings support this expectation: a clustered chi-square test indicates a significant association between job appeal and engineering career intent (chi-square = 27.62; $p < 0.001$), where mean appeal among those with engineering career intent was 0.77 compared to 0.66 among those without engineering intent. A second realism test checked to ensure that no specific job profile (among the 24 possible profile configurations) was universally unappealing to participants. Figure 10 in the appendix presents mean job appeal values (with 95% confidence intervals) for all job configurations. As shown, the least-appealing job profile configuration was found to have a mean appeal value of 0.57 (i.e., it was rated as appealing 57% of the time). Hence, a substantive subset of participants found the least-appealing jobs to be appealing to them. These realism checks give confidence that the set of experimental job profiles vary within reasonable bounds.

Finally, we assessed participants' recognition of job attribute variations via manipulation checks shown in Table 7 in the appendix. As expected, participants' recognition of meaningful differences across job attributes was notably higher for the manipulated attributes (0.63 mean response) compared to the non-manipulated attributes (0.11 mean response). For each manipulated attribute, we tested whether the manipulation check produced significantly higher recognition responses compared to the checks for each non-manipulated attribute by running pairwise Wilcoxon signed-rank tests for each of the 16 possible comparisons. Table 8 of the appendix presents the results of these tests, showing a Z-statistic and significance level for each pairwise comparison. In all cases, the mean recognition responses were found to be significantly higher for the manipulated attributes than for the non-manipulated attributes (at $p < 0.001$).

Job Preference Interactions Analysis

Following the job preferences analysis for the full sample, we next examined how job attribute manipulations may interact with student characteristics to influence preference responses differently across theoretically relevant subgroups of students. In conjoint experiments, subgroup comparative analyses can be carried out in two different ways: by repeating the type of regression analysis used to generate Fig. 2 separately for conditional subgroups within the sample and then comparing the resulting AMCEs across subgroups, or by testing for interaction effects between participant-specific characteristics and job attribute manipulations using interaction terms in a full sample regression. We demonstrate the former type of analysis in this section and the latter approach subsequently in *Aggregate job preferences model*. The two approaches serve different illustrative purposes. The conditional subset approach allows researchers to isolate and visualize manipulations' effects upon specific subgroups' preferences. We use this approach first to individually test each hypothesized interaction listed in Table 1. Full sample regressions with interaction terms, meanwhile, enable testing for statistically significant differences of manipulations' effects across many subgroups simultaneously. This latter approach allows us to build an aggregate model to investigate the central inquiry of this study: if interactions between student characteristics and job attributes are statistically significant in an aggregate full sample model, such a finding would support the proposition that variance in engineering students' job preferences cannot be fully explained by the sum of the student-specific and job-specific variables' independent effects on job preference. Rather, models accommodating both the supply-side and demand-side variables, in interaction with each other, are needed to more thoroughly understand engineering students' job preferences. We report on this central investigation later in *Aggregate job preferences model*.

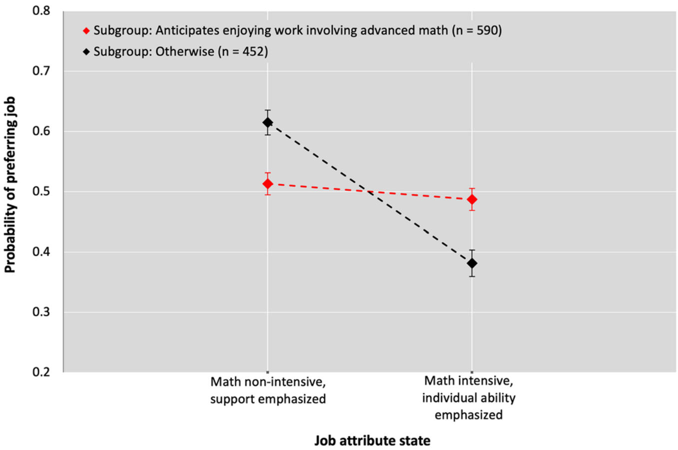


Fig. 3 Interaction analysis: anticipation of enjoying work involving advanced mathematics and jobs' mathematics intensity

To examine each hypothesized job preference interaction (in Table 1), we began by graphically plotting estimates of conditional job preference probabilities (with 95% confidence intervals) for the key participant subgroups at each state of the pertinent job attribute. Figure 3 shows such a plot for the mathematics intensity manipulation for the key subgroups involved in Hypothesis 1: those who anticipate enjoying work involving advanced mathematics and those who do not. Here, as in each case where a subgroup's defining variable is a scale measure, we form the comparative subgroups based upon dichotomizing the scale measure into high and low states associated with values above the scale midpoint and otherwise, respectively. To formally test for the significance of the interaction effect shown graphically in the figure, we used Stata's *Suest* post-estimation command to compare the math intensity manipulation's coefficients across the conditional regressions for each of the subgroups (i.e., we compare the subgroups' conditional AMCEs). As shown in Fig. 3, we observe an asymmetric preference effect in response to this manipulation across the subgroups: those who do not anticipate enjoying work involving advanced math exhibit a substantive and significant drop in job preference probability when informed that jobs entail intensive math, while the comparison subgroup exhibits no statistically significant change in preference probability. In this latter case, for those who anticipate enjoying work involving advanced math, the probability of job preference is near 0.5 at both math intensity attribute states, suggesting ambivalence about this job attribute. Yet, for the first subset, we observe a drop in estimated probability of job preference of −0.23 (from 0.61 to 0.38) between math-non-intensive and math-intensive jobs, respectively. The post-estimation coefficient comparison test finds the math intensity manipulation's coefficients to be significantly different ($p < 0.001$) across these two student subgroups. This finding supports our hypothesis of a significant job preference interaction between individuals' perception of math enjoyment and their informedness of jobs' math intensity (Hypothesis 1).

We tested the other hypotheses in Table 1 in the same manner as in the preceding example, next examining the interaction between individuals' anticipation of early-career advancement into leadership roles and their awareness about leadership growth opportunities at engineering jobs. Figure 4 shows plots of conditional job preference probabilities for the pertinent sample subgroups. For both subgroups, probabilities of job preference were

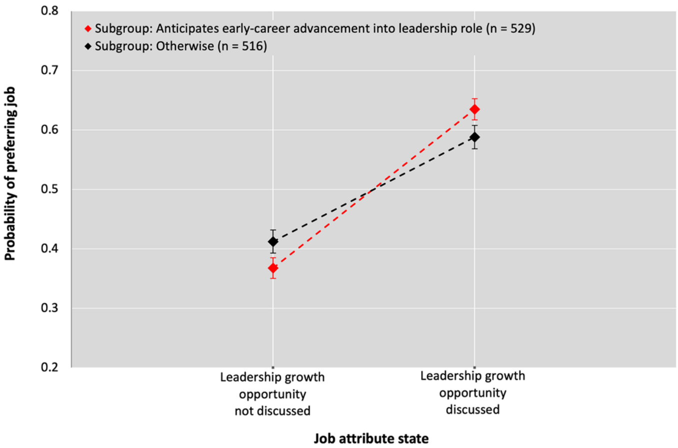


Fig. 4 Interaction analysis: anticipation of early-career advancement into leadership role and jobs' leadership growth opportunity

estimated for two job attribute states: cases where jobs' leadership growth opportunities are and are not discussed. As shown, those participants who anticipate early-career leadership roles demonstrate a more substantial increase in job preference probability when informed about leadership growth opportunities compared to the other participants. In the former case, participants' estimated job preference probability increases from 0.37 to 0.64 upon becoming informed of these opportunities (a probability change of + 0.27), while in the latter case, estimated job preference probability increases by a more modest + 0.18. We again assess the statistical significance of this interaction by comparing attribute state variable coefficients between the conditional regressions, finding the difference to be significant ($p < 0.001$). This result supports our hypothesis of a significant interaction between individuals' anticipation of early-career advancement into a leadership role and individuals' informedness of jobs' leadership growth opportunities (Hypothesis 2).

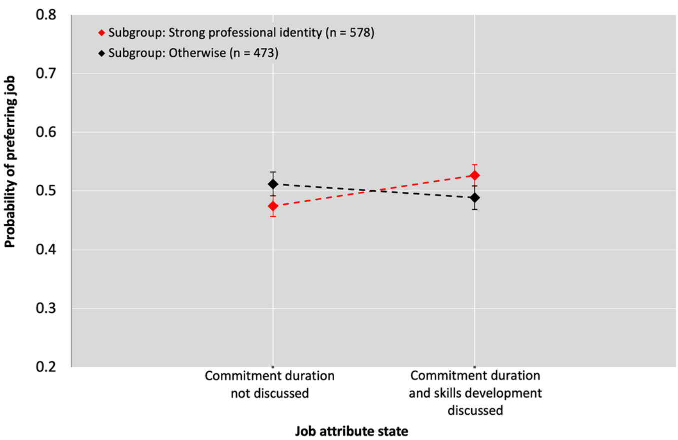


Fig. 5 Interaction analysis: strength of professional identity and jobs' expected commitment duration

We next examined two interaction effects between participant characteristics and jobs' expected commitment duration. First, we assessed the interaction of participants' strength of professional identity with manipulation of this job attribute. Figure 5 shows conditional job preference probabilities for those who identify with a specific profession and for those who do not; here, both subgroups' probabilities of preferring jobs were estimated for jobs with and without expressed commitment expectations (coupled with specialized training). Figure 5 shows differences in the job attribute manipulations' effects, indicating that those with a strong professional identity reacted more positively to an expected commitment duration (a + 0.05 change in preference probability) compared to those with a comparatively weak professional identity (a statistically insignificant negative response). This difference in job manipulation effect upon these groups was found to be statistically significant ($p < 0.01$; based on a comparison test of coefficients for the job attribute variable between subgroup-conditional regressions), supporting our hypothesis of a significant interaction between individuals' strength of professional identity and informedness of jobs' expected commitment duration (Hypothesis 3). Secondly, we assessed the interaction between participants' satisfaction with creative opportunities in engineering work and jobs' commitment expectations (Fig. 6). Here we again found a difference in the commitment attribute's effect across subsets, where those who are satisfied with creative opportunities in engineering exhibited a + 0.05 change in estimated probability of job preference when informed of commitment expectations, while those not satisfied with creative opportunities exhibited a near-flat response. This difference in manipulation effect was also found to be statistically significant ($p < 0.05$), in support of our hypothesis of an interaction between individuals' satisfaction with creative opportunities at engineering jobs and informedness of jobs' expected commitment duration (Hypothesis 4).

Finally, we examined interactions between gender and social characteristics of engineering jobs. Here we conducted two analyses, the first of which is presented in Fig. 7: gender-conditional job preference probabilities for the manipulation from individualistic to collaborative job types. As shown, both participant subgroups reacted positively to this job manipulation, on average, but women reacted distinctly more positively, exhibiting a + 0.26 change in preference probability (compared to + 0.16 for those identifying otherwise) as

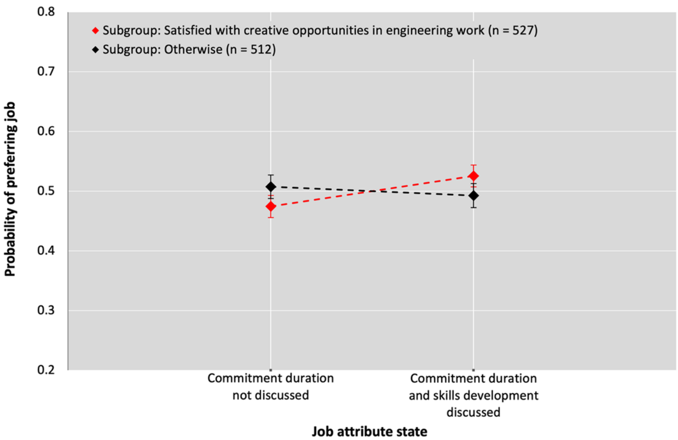


Fig. 6 Interaction analysis: satisfaction with creative opportunities in engineering work and jobs' expected commitment duration

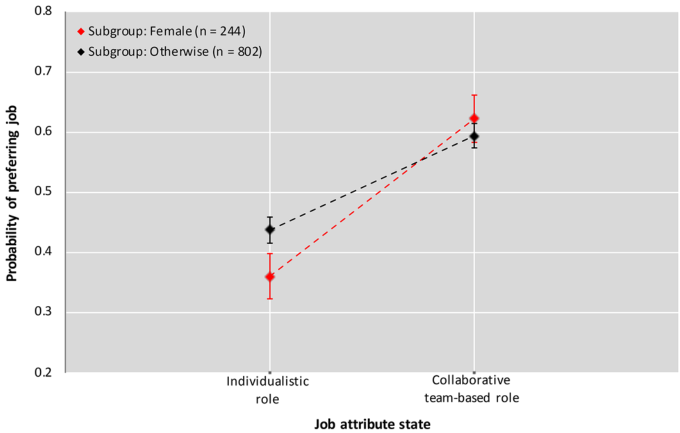


Fig. 7 Interaction analysis: gender with jobs' social characterization (individualistic vs. collaborative)

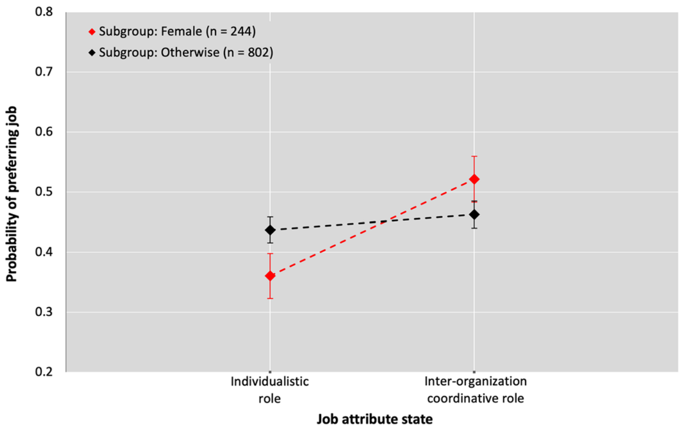


Fig. 8 Interaction analysis: gender with jobs' social characterization (individualistic vs. coordinative)

jobs' social characterization shifted from individualistic to collaborative. This difference was found to be statistically significant ($p < 0.01$, based on a comparison test of coefficients for the job attribute variable between subset-conditional regressions). We next conducted a similar analysis for gender's interaction with the manipulation from individualistic to coordinative job types (Fig. 8). Here we again see that women responded distinctly more positively, exhibiting a $+0.16$ change in preference probability (compared to a near-flat response for those identifying otherwise). We again find this gendered difference in manipulation effect to be statistically significant based on a coefficient comparison test between subset-conditional regressions ($p < 0.001$). We hypothesized that gender would interact significantly with informedness about social components of engineering work to influence engineering students' attraction to jobs (Hypothesis 5). The findings from both experimental manipulations pertaining to jobs' social characteristics support this hypothesis.

In tabular rather than graphical form, Table 9 in the appendix summarizes conditional AMCEs computed for each of the key subgroups assessed in this section. Table 9,

Table 5 Aggregate models of job attribute manipulations' effects on job preference, with and without interactions

Dependent variable: job preference independent variables	Model 1	Model 2
Job attribute A, mathematics intensity	− 0.119***	− 0.419***
	(0.014)	(0.041)
Job attribute B, leadership growth opportunity	0.222***	0.083
	(0.013)	(0.048)
Job attribute C, commitment duration expectation	0.018	− 0.118*
	(0.013)	(0.056)
Job attribute D1, social characterization as collaborative and team-based	0.180***	0.159***
	(0.016)	(0.018)
Job attribute D2, social characterization as inter-organization coordinative	0.056**	0.024
	(0.017)	(0.019)
Anticipates enjoying work involving advanced mathematics		− 0.062*** (0.008)
Strong professional identity		− 0.015 (0.008)
Anticipates early-career advancement into leadership role		− 0.013** (0.005)
Satisfied with creative opportunities in engineering work		− 0.010 (0.005)
Female		− 0.067** (0.022)
(Anticipates enjoying work involving advanced mathematics) × (Job attribute A)		0.130*** (0.017)
(Anticipates early-career advancement into leadership role) × (Job attribute B)		0.030** (0.010)
(Strong professional identity) x (Job attribute C)		0.032* (0.015)
(Satisfied with creative opportunities in engineering work) × (Job attribute C)		0.015 (0.010)
(Female) × (Job attribute D1)		0.093* (0.038)
(Female) × (Job attribute D2)		0.140*** (0.038)
Constant	0.359***	0.657***
	(0.016)	(0.044)
Incremental F-test		9.37***
Adjusted-R^2	0.086	0.102
Total observations	6220	6000
Clusters	1054	1014

1. Both models are linear regression models; robust standard errors (clustered by participant) are in parenthesis

2. The reduction in observation count between Model 1 and Model 2 is due to the addition of variables to Model 2: only participants who completed all survey questions corresponding to all variables in Model 2 are included there

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$ (two-tailed tests)

furthermore, presents the full matrix of conditional AMCEs representing each of these subgroups' responses to each of the job attribute manipulations.

Aggregate job Preferences Model

We constructed an aggregate conjoint job preferences model (shown in Table 5) encompassing all six of the interaction effects that we previously assessed individually. We again employed linear regression in the aggregate model based on the modeling considerations discussed previously (see: *Data collection, verification, and analysis*). Model 1 within this table, which includes only job attribute manipulation terms, represents the baseline model introduced earlier in Fig. 2. Model 2 in Table 5 includes the interaction terms for the six interactions along with the participant-specific independent variables involved in these interactions. Observing interactions' effects is not as straightforward in this context as it was in our graphical inspection of individual interaction effects. Here, a given interaction's effects can manifest in the interaction terms themselves, as well as in as changes in the coefficients for any of the independent variables involved in an interaction (i.e., attribute manipulation indicator variables and participant-specific independent variables). Based on the outcome of Model 2, we find that five of the six incorporated interaction effects are statistically significant in the aggregate model. Further, an incremental F-test between Model 1 and Model 2 produced a statistically significant F-statistic ($F = 9.37$, $p < 0.001$), indicating that the inclusion of interaction effects in Model 2 explains additional variance in students' job preferences compared to Model 1.

One of the previously-tested interaction effects, that associated with Hypothesis 4 (satisfaction with creative opportunities in engineering work interacted with jobs' expected commitment duration), which was significant when tested independently ($p < 0.05$), is shown to lose its significance in the aggregate model (Model 2). Here it is notable that Model 2, with its larger independent variable count, employs a slightly smaller sample size compared to models containing only the job attribute independent variables (see: Note 2 of Table 5). Nonetheless, the findings from Model 2 lead us to conclude that Hypothesis 4, unlike the other five hypotheses, is not supported in the aggregate model.

In sum, through a conjoint job preferences experiment, we found that several interaction effects between engineering students' individual characteristics and certain realistically varying job attributes significantly influence students' job preferences. A job preferences model incorporating these interactions is shown, via a significant incremental F-test, to be an improved model of engineering students' job preferences compared to a model where these interactions are omitted. These results support the study's central proposition: that the general trends in job preferences exhibited by a broad sample of engineering students contain variance that can be further explained by accounting for significant differences in how key subsets among the students uniquely react to realistic differences across engineering jobs.

Limitations of Results and Considerations for Future Work

Research design limitations should be taken into consideration when interpreting our findings. First, readers should note that the constraints we placed upon recruiting our participant sample reflected a conscious tradeoff. Our choice to sample exclusively mechanical engineering majors allowed us to minimize potential confounding effects on attitudes toward working at engineering jobs that could have been present if the study's participants faced differing job market conditions across varied engineering subfields. This constraint upon participants' degree field also allowed the study's experimental job profiles to include realistic, rather than generic, job content. In support of generalizability, however, the job manipulations we tested within the discipline-specific job profiles were drawn from the broad literature on engineering practice and pertain to job choice considerations faced by students across a wide array of engineering fields. Yet, since our dataset does not allow us to empirically confirm that these results will generalize across diverse disciplines, we note that follow-on work that assesses replicability of these findings in different degree fields could increase confidence in the generalizability of our findings.

Beyond transdisciplinary generalization, we also note that follow-on work may be prudent to examine replicability across a broader range of educational pathways into engineering careers. While the nine institutions we examine here represent geographic diversity and span public and private institution types, this study's institutional sample nonetheless skews toward more traditional and historically elite institution types (for instance, seven of the nine universities are members of the esteemed Association of American Universities). Future work assessing the extent to which the engineering job preference effects examined here pertain to students on different pathways, such as those tied to smaller and less research-intensive institutions or to part-time degree programs would complement the findings in this study.

Finally, readers should be aware that participants' stated preferences for job profiles in our experiment cannot be confirmed to correspond directly to real-life job choice behaviors. Scholars have highlighted the importance of survey context in achieving valid findings in attempts to predict real-life choices (Berinsky, 2017; Kagan, 2017). Kagan (2017), for instance, cautions against conducting studies on human attitudes or behaviors in contexts where participants are far removed from the real-life phenomena being investigated—such as by asking participants to express how they feel about a threat that is not real or how they would respond if they were someone or some place they were not—citing potentially poor external validity of findings from such studies. We selected our sample and research context to mitigate this type of concern. We did not ask participants to envision being anyone they were not; rather, our approach measured participants' job preferences while in their own shoes as senior year engineering students at a time when the job market was likely on their minds. Follow-on research, however, could further increase confidence that the preference effects identified in our study translate to real job pursuit behaviors by aligning data collection and real-life job pursuits even more closely. Such could potentially be accomplished by studies that utilize real recruitment or job selection contexts as research sites (e.g., university career fairs, career services offices or online resources, etc.) and examine candidates' job pursuit behaviors in these contexts.

Discussion and Conclusions

Our findings shed light on how university students' preferences for engineering jobs are shaped by their awareness of key differences among these jobs. The findings also elucidate the manners in which job attributes interact with student characteristics – such as students' beliefs and expectations as they approach the job market – to influence their job preferences. These results suggest an opportunity for collegiate educators to play a greater role in strengthening and diversifying the engineering workforce, such as through increasing students' awareness of the variety across types of engineering jobs and by helping students overcome self-assessment biases and exposure to stereotypes about engineering work. Our findings also highlight how differences in the detailed information conveyed about engineering jobs during employers' recruitment processes can strengthen or reduce students' attraction to jobs. Finally, our study contributes empirical evidence in support of others' prior analyses: that lack of awareness of differences across engineering jobs may be a substantive source of variance in job preferences among those in engineering pathways (e.g., Brunhaver et al., 2013; Craps et al., 2021; Perlow & Bailyn, 1997).

Among our study's overall sample of U.S. senior year mechanical engineering students, we detected preference trends suggesting students' attraction to certain engineering jobs over others: jobs that are comparably lower in mathematics intensity, jobs that are tied to specific leadership growth paths, and jobs that are more socially collaborative or coordinative. These broad trends must be interpreted with caution. They are generalizations at our full-sample level and should not be taken to imply, for instance, that few engineering students are attracted to jobs involving intensive mathematics, or that few students prefer individualistic work. Quite the contrary: in instances where the randomized survey presented participants with pairs of job profiles where one of the two featured intensive math, participants expressed greater preference for the math-intensive job 37.3% of the time. And in cases where participants saw job profile pairs where one of the two profiles centered on individualistic work, participants expressed preference for the individualistic job 36.9% of the time. Therefore, while it may be useful to know what types of jobs majorities of engineering students prefer, this study's primary research contribution lies in identifying the nuanced job preference patterns that underlie these broader trends. We conclude this paper by discussing these patterns' implications relative to key engineering workforce development issues and higher education's (and employers') opportunities for resolving or mitigating such.

We found, for instance, that responses to manipulation of jobs' mathematics intensity showed notable asymmetry between student subsets (Fig. 3). Those who anticipated enjoying work involving advanced math (55.9% of the sample) exhibited an insignificant difference in preference probability between jobs featuring low and high math intensity, while those who did not anticipate enjoying work involving advanced math (42.6% of the sample) exhibited a significant drop in preference probability when informed that jobs involved intensive math. This asymmetric effect is noteworthy because it suggests that under-informedness about jobs' mathematics content may not merely introduce random noise in student-job matching; rather, it could cause a skewed mismatching of students to jobs. Literature suggests that engineering work carries a reputation as math-intensive (NAE, 2008; Winkelman, 2009); yet, studies also indicate that engineering positions differ substantively in terms of actual math intensity (Alpers, 2010; Goold, 2012; Kent & Noss, 2002). If under-informed about jobs' math intensity, students may default to assuming that a given engineering job is more math-intensive than it really is. In turn, our findings suggest that those less assured of their enjoyment of working with math could be more likely than their peers to avoid engineering jobs they might excel at—an implication salient to gender diversity in light of prior research. Past studies have found that, net of actual math ability, women students possessed lower mathematics confidence, on average, compared to men (Correll, 2001; Ellis et al., 2016), a self-assessment bias linked to gendered cultural beliefs about roles and abilities (Correll, 2001, 2004; Hyde et al., 1990). Our findings therefore suggest that women, if uninformed about accurate details of a job, could be disproportionately dissuaded from taking engineering positions until this gendered math self-confidence gap is closed.

Concerns about mismatching of students and jobs due to under-informedness about math intensity is not limited to gender equity considerations. All participants in this study's sample were on track to successfully complete an accredited engineering degree and therefore possessed sufficient mathematics aptitude for that accomplishment. Yet, our results suggest that any of the sample's substantial subset who did not anticipate enjoying mathematical work could be more susceptible to avoiding engineering jobs than their peers. These findings imply that educators should better illustrate differences in how math is used in engineering practice compared to engineering school, as has been suggested (Winkelman, 2009). Results also suggest an imperative for employers to express math requirements accurately in job descriptions. Certainly, employers aspiring to hire computational specialists should be clear about intensive mathematical obligations of those roles, but employers looking to hire generalists should be cautious that they may inadvertently push away qualified candidates if job descriptions include boilerplate language about mathematical or analytical requirements beyond what are needed. Employers, in short, should take steps to create job postings that are unique for specialist and generalist roles in ways that appropriately distinguish these roles.

The job preference patterns identified in response to jobs' leadership growth opportunities carry notably different implications compared to those found for jobs' math intensity. Though key student subsets also demonstrated significant differences in the magnitudes of job preference probability effects depending on whether leadership opportunities were expressed in job profiles (Fig. 4), these effects were both in the positive direction; in fact, all examined student subsets reacted positively and significantly when jobs were manipulated to include advancement opportunities into leadership roles (Appendix Table 9). This finding is important in light of evidence that engineering employers seek to boost recruitment of candidates with leadership abilities and aspirations (Cappelli, 2015; Salzman & Lynn, 2010). Our results suggest that heightening university students' awareness of leadership growth opportunities at engineering jobs could enhance the attractiveness of persisting in engineering, on average, across the broad candidate pool. This is not to say that all students should be pushed toward leadership roles; recall, the experiment's job attribute statement for "leadership growth opportunities" described the opportunities as "[for] qualified candidates…if interested" (Table 2). Our findings, rather, suggest little or no downside to increasing all students' awareness of leadership opportunities at engineering jobs, such as via the growing movement among engineering schools to include engineering leadership courses or programs (for a review, see: Klassen et al., 2016). These results also suggest that job descriptions that do not mention opportunities for future growth into leadership roles are at a general disadvantage in attracting candidates compared to those that do. We are not suggesting employers should falsely advertise opportunities if they do not exist. Rather, where possible, employers should incorporate these growth opportunities into both the design and marketing of positions based on this information's positive effect on positions' attractiveness.

Students' job preferences in response to manipulation of jobs' commitment expectations also suggest that different student subgroups respond differently to the manipulation (Figs. 5 and 6). When examined individually, two key subgroups—those with strong professional identities and those satisfied with opportunities for creativity in engineering work—were observed to react positively, on average, to job profiles that included an expected commitment duration coupled with training and development of specialized skills. Meanwhile, students who did not belong to either of these groups did not respond positively; their responses were statistically similar regardless of jobs' commitment expectations.

Our findings of subgroups' differing responses to the commitment expectations manipulation, however, only partially support our pertinent hypotheses from Table 1. In the case of Hypothesis 3, both the independent interaction analysis (Fig. 5) and the aggregate model (Model 2 in Table 5) indicate significance of the anticipated interaction between students' strength of professional identity and jobs' expected commitment duration toward job preference. Here, even for the case of students with strong professional identities, we were surprised not to have measured more of a negative response to commitment expectations given literature documenting negative impacts of employer-imposed mobility constraint upon job appeal (Marx et al., 2015). Yet, we note that the commitment expectation manipulation operationalized in this study was a compound manipulation: not only did the manipulation impose commitment expectations but it also discussed employer-sponsored skills development tied to work on advanced projects. As explained in *Conceptualization and operationalization of job attribute manipulations*, the choice to include both of these features was intentional based on the literature: precedent suggests that employer-imposed commitment expectations are more legally viable when coupled with specialized skill development in areas tied to firms' competitive advantage (Lester, 2001). It is plausible, though, that including both elements in the manipulation may have tempered negative responses, especially considering findings of an association between employers' sponsorship of skills development and increased retention at jobs (Benson et al., 2004). Should this experiment be repeated, we recommend incorporating three job attribute states into this manipulation. A three-state manipulation could test for the effect of imposing a commitment expectation both with and without the additional element of skill development. Meanwhile, despite supporting evidence in the isolated interaction analysis (Fig. 6), we note that the aggregate job preferences model (Model 2 in Table 5) does not sustain statistically significant support for Hypothesis 4 (the interaction between students' satisfaction with creative opportunities in engineering work and jobs' expected commitment duration), indicating a weak interaction. Based on the evidence toward Hypothesis 3, however, we do find that the imposition of a commitment expectation produces significant differences in job attraction among candidates; specifically, that those students who already possess a strong professional identity are more accepting of commitment duration expectations at jobs compared to their peers.

Finally, we observed gendered differences in the ways individuals responded to information about jobs' social characterizations (Hypothesis 5), as was expected based on our literature review. We found that women students exhibited a greater likelihood of preferring engineering jobs upon being informed that jobs were rooted in collaborative or coordinative work rather than in individualistic work (Figs. 7 and 8). These results carry potentially salient implications toward strengthening gender diversity in the engineering workforce. Considering engineering's historic reputation as centering on individualistic technical work (Bucciarelli & Kuhn, 1997; Seron et al., 2016, 2018), we suspect that if students are under-informed about the details of engineering jobs, they might default to assuming the jobs are more individualistic than they really are. Such a tendency, in turn, suggests a disproportionate negative impact on women's interest in engineering jobs, given women's more negative views of individualistic engineering jobs compared to men's. Our results support certain courses of action that could strengthen women's interest in engineering jobs. First, educators should continue refining the engineering educational experience, particularly student project team experiences, to validate conceptions of engineering work that place social, collaborative, and coordinative components at the heart of the discipline (see, e.g., Cech, 2015). Employers, meanwhile, should highlight collaborative and coordinative aspects of roles during recruiting and hiring processes for engineering positions. While our findings indicate that women responded more positively to information about these aspects of roles than men did, our results do not indicate a negative response from men to this information – in fact, none of the subsets of engineering students we examined exhibited a negative reaction to such information (Appendix Table 9). There appears to be little downside to recruitment efforts that highlight engineering jobs' social elements.

Our findings, in sum, point to awareness of engineering jobs' variety as a significant source of variance in engineering students' attraction to working in their field of study. Prior studies on engineering students' persistence into the engineering workforce have largely focused on student-specific factors as explanatory variables, often assuming engineering work itself to be homogenous. Our findings suggest that research in this area can more fully examine students' persistence into engineering jobs if the variety in engineering work is accounted for in research designs. Moreover, recent U.S. education policy has focused on encouraging students toward engineering or STEM careers broadly, while directing little attention to students' placement into (and satisfaction with) specific and differing engineering jobs after college graduation. Here, too, our results suggest that improved student-job matching can be accomplished with more emphasis placed on informing candidates about the substantive differences that exist across roles in engineering. These conclusions complement those from prior works suggesting a larger role for higher education in growing engineering students' occupational awareness and, consequently, toward strengthening career fit and satisfaction (Brunhaver et al., 2013; Craps et al., 2021; Xu, 2013). Celebrating the differences among engineering jobs, while continuing to celebrate differences among students, appears to be critical in education and recruitment efforts aimed at strengthening and diversifying the engineering workforce, as well as in conducting more informed research.

Appendix

See Tables 6, 7, 8, 9 and Figs. 9, 10.

Table 6 Survey questions for student-specific independent variables from supply-side model of engineering persistence (Magarian & Seering, 2022; see also details therein regarding survey question development and validation)

Survey questions: key independent variables

Anticipates enjoying work involving advanced mathematics

Which of the following better describes your relationship with mathematics?

Please check only one; assume " advanced mathematics" is within the bounds of your major's curriculum

[A job that regularly requires use of advanced mathematics concepts would be enjoyable for me]

[A job that regularly requires use of advanced math would not be enjoyable for me]

[I' m unsure]

Strong professional identity

When you envison your ideal career, is it based upon a specific profession? (e.g., doctor, engineer, lawyer, consultant, artist, etc.)

[Yes] [No] [Unsure/can' t envision ideal career]

Anticipates early-career advancedment into a leadership role

How likely is it that you will be appointed to a formal leadership position early in your career? (e.g., by age 25)

Please circle the appropriate number on the scale:

[7-pt scale: very unlikely, unsure, very likely]

Satisfied with creative opportunities in engineering work

How satisfied are you with the availability of job opportunities that allow graduates to engage in creative design work in engineering jobs after college? Please circle the appropriate number on the scale:

[7-pt scale: entirely unsatisfied, unsure, entirely satisfied]

Survey questions: other independent variables & controls

Expected occupational outcome

Which one of the following represents how you will most likely begin your career journey after undergraduate graduation?

[Work as an engineer]

[Work in product management, project management, technical consulting, or quantitative analysis]

[Work in management consulting, finance, or venture capital]

[Work other: ____________]

[Grad school, then work as an engineer]

[Grad school, then work in product management, project management, technical consulting, or quantitative analysis]

[Grad school, then work in management consulting, finance,or venture capital]

[Grad school, then pursue a career in academia]

[Grad school, then other: ____________]

[Other: ____________]

Gender

What is your gender? [Female] [Male] [_________]

Race

How do you identify yourself by race and/or ethnic origin?

[American Indian or Alaska Native] [Asian (Incl. Indian subcontinent)] [Black or African American]

[Hispanic or Latino/Latina] [Native Hawaiian or Pacific Islander] [White] [_________]

Varsity athletics participation status

Have you participated in a collegiate varsity athletics program? [Yes] [No]

If "Yes," how many seasons wil you have participated in before graduating? [_________]

Table 6 (continued)

Greek life participation status
As an undergraduate, were you a member of a fraternity or sorority? [Yes] [No]
If "Yes," did you hold an elected leadership position within the fraternity or sorority? [Yes] [No]
Undergraduate major
Are you a Mechanical Engineering student? (either by degree major or by home department) [Yes] [No]
If "No," then what is your home department? [_________]
Degree completion date/status
When do you expect to complete your bachelor's degree? [Month: _________] [Year: _________]

Table 7 Survey questions for experimental manipulation checks

Survey questions: conjoint experiment manipulation checks
Please tell us about any *meaningful differences* that existed among the above job postings in any of the attributes below
Place a check next to any/all of the attributes that differed meaningfully among the different jobs:
[ ] Company size
[ ] The amount or intensity of mathematical work associated with the job
[ ] Company age
[ ] Expected commitment duration in the role (e.g., how long you will stay at the role you' re hired into)
[ ] The degree of solitary work versus collaborative work
[ ] Salary
[ ] Opportunity to be promoted into leadership positions
[ ] Other; please specify: ____________________________

Table 8 Results from survey experiment manipulation checks

Z-statistics from pairwise comparisons of responses to attribute manipulation recognition checks

Manipulated attributes	Non-manipulated attributes:			
	Company size	Company age	Salary	Other
Mathematics intensity	18.51***	21.87***	13.38***	20.48***
Leadership growth opportunity	23.96***	26.07***	20.72***	24.74***
Commitment duration expectation	18.16***	21.27***	13.40***	19.82***
Social characterization of work	24,51***	26.71***	20.89***	28.82***

Z-statistics are from Wilcoxon signed-rank tests of differences. The tests compare binary recognition responses between attributes: those attributes that were actually manipulated and those that were not manipulated. Positive and significant Z-statistics indicate significantly higher recognition of the manipulated attribute over the non-manipulated in each

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$ (two-tailed tests)

Table 9 Subgroup comparisons: job attribute manipulations' effects on probability of job preference

Participant characteristics (conditional subgroups)	Job attribute manipulations[a, c]				
	Mathematics intensity	Leadership growth opportunity	Expected commit duration in role	Social characterization of work	Social characterization of work
	Non-intensive with support to intensive and individualistic	Not discussed to discussed	Not discussed to discussed	Individualistic to collaborative	Individualistics to inter-organization coordinative
Full sample (n = 1054)	−0.119***	0.222***	0.018	0.180***	0.056**
	(0.014)	(0.013)	(0.013)	(0.016)	(0.017)
Expecting to work as an engineer (n = 745)	−0.078***	0.225***	0.034*	0.175***	0.043*
	(0.017)	(0.015)	(0.016)	(0.019)	(0.020)
Otherwise (n = 252)	−0.251***	0.210***	−0.025	0.213***	0.118***
	(0.027)	(0.026)	(0.025)	(0.033)	(0.031)
Anticipates enjoying work involving advanced mathematics (n = 590)	−0.026	0.229***	0.038*	0.159***	0.053*
	(0.018)	(0.017)	(0.018)	(0.021)	(0.023)
Otherwise (n = 452	−0.233***	0.204****	−0.001	0.206***	0.061*
	(0.021)	(0.020)	(0.020)	(0.024)	(0.025)
Anticipates early-career advancement into leadership role[b] (n = 529)	−0.150***	0.267***	0.033	0.178***	0.074**
	(0.020)	(0.017)	(0.018)	(0.021)	(0.022)
Otherwise (n = 516)	−0.086***	0.176***	0.005	0.186***	0.039
	(0.020)	(0.019)	(0.020)	(0.024)	(0.025)
Strong professional identity (identifies with a specific profession) (n = 578)	−0.078***	0.225***	0.052**	0.184***	0.044
	(0.019)	(0.017)	(0.018)	(0.022)	(0.023)
Otherwise (n = 473)	−0.165***	0.223***	−0.023	0.178***	0.074**
	(0.020)	(0.019)	(0.020)	(0.023)	(0.024)

Table 9 (continued)

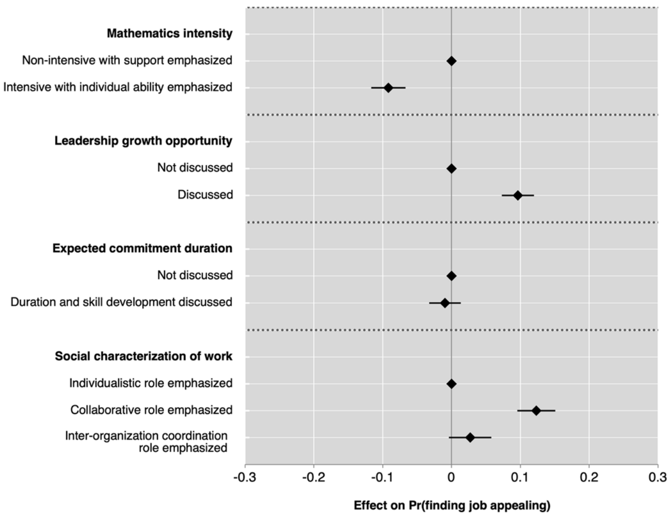
Participant characteristics (conditional subgroups)	Job attribute manipulations[a, c]				
	Mathematics intensity	Leadership growth opportunity	Expected commit duration in role	Social characterization of work	Social characterization of work
	Non-intensive with support to intensive and individualistic	Not discussed to discussed	Not discussed to discussed	Individualistic to collaborative	Individualistics to inter-organization coordinative
Satisfied with creative opportunities in engineering work[b] (n = 527)	−0.095***	0.233***	0.051**	0.156***	0.061*
	(0.021)	(0.018)	(0.018)	(0.022)	(0.024)
Otherwise (n = 512)	−0.141***	0.216***	−0.015	0.205***	0.051*
	(0.019)	(0.019)	(0.020)	(0.023)	(0.024)
Female (n = 244)	−0.148***	0.181***	−0.026	0.262***	0.161***
	(0.030)	(0.027)	(0.028)	(0.033)	(0.032)
Otherwise (n = 802)	−0.111***	0.233***	0.033*	0.157***	0.026
	(0.016)	(0.015)	(0.015)	(0.0180)	(0.019)

[a] The values in each cell are estimates of Average Marginal Component Effects (AMCEs) on the probabilities that subjects from conditional subgroups will prefer a job based on differences in job attribute states. Robust standard errors are in parentheses under AMCE values. Subgroup sample sizes are shown next to subgroup labels in the left most column; these values are sometimes lower than those reported in Table 4 because participants needed to have responded to both the subgroup categorization questions and the job profile assessment questions to be counted here

[b] These variables were dichotomized from 7-pt scale variables for the purposes of subgroup comparison; this split distinguishes those who responded with values above the scale midpoint from the others

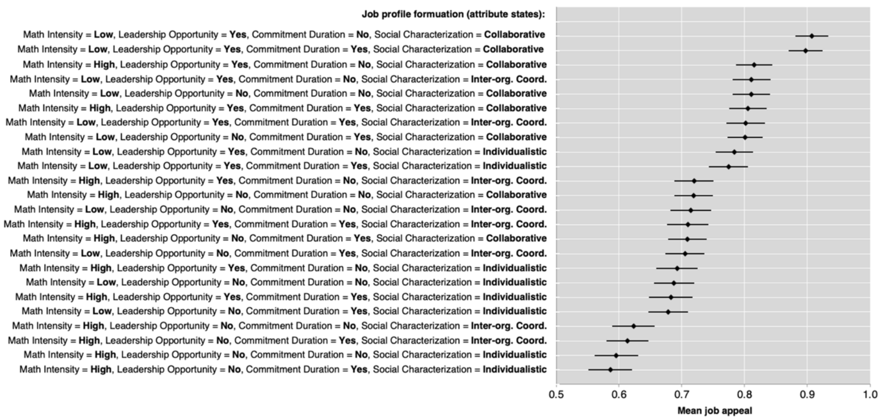
[c] Significance levels shown here are for subgroup-specific conditional AMCEs; they do not represent subgroup-to-subgroup comparison tests

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$ (two-tailed tests)



Notes:
This plot shows estimates of the Average Marginal Component Effects (AMCEs) of randomly manipulated job attributes on the probability of a job being found to be appealing. Horizontal bars represent 95% confidence intervals. The points without horizontal bars denote the attribute state that is the reference category for each attribute. The plot is based upon this study's full sample (6,112 job appeal ratings from 1,056 unique participants). Here, job appeal refers to any job rating above the midpoint of the 7-point scale showin in Figure 1.

Fig. 9 Robustness check: job attribute manipulation effects based on dichotomized appeal scale data



Notes:
This plot shows estimates of mean job appeal ratings for each job profile formualtion. Mean job appeal is based on the dichotomous form of the job appeal variable: appeal equals one if participants rated a job's appeal above the midpoint of the scale shown in Figure 1 and where appeal equals zero otherwise. The job profile formulations shown here represent the exhaustive set of all profiles tested in this study. Horizontal bars represent 95% confidence intervals. The plot is based on the study's full sample of participants who submitted job appeal ratings (6,112 observations from 1,056 unique individuals).

Fig. 10 Mean job appeal ratings for the exhaustive set of experimental job profile formulations

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Declarations

Conflict of interest The authors declare that they have no conflicts of interest.

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