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Research Article

Does Open Innovation Open Doors for Underrepresented Groups to Contribute to Technology Innovation?: Evidence from a Space Robotics Challenge

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ABSTRACT

Diversity, equity, and inclusion (DEI) are increasingly being recognized as important policy goals for organizations across government and the industry. Improved DEI has been linked to both substantive improvement in innovation performance and societal good. However, despite a stated emphasis on DEI, progress has not kept up with aspirations. One indirect policy approach that holds promise is wider adoption of Open Innovation (OI) as part of an innovation toolkit. Proponents contend that OI reduces barriers to entry and garners productive contributions from diverse contributors. While there is anecdotal support for the diversifying potential of OI, so far, there is a dearth of empirical evidence connecting OI to DEI with consideration of performance outcomes, beyond `winners´. To study this link directly, this article leverages data from a previously conducted unique field experiment that explicitly tracked the population of potential solvers and their performance on a National Aeronautics and Space Administration (NASA) space robotics problem. We found that while OI attracted different solvers than the reference internal workforce, there was important variation in both the extent and direction of the observed differences, with respect to attributes of DEI. For instance, OI attracted proportionally fewer female solvers than the already male-dominated space workforce; and that proportion decreased further among solvers providing quality solutions. On the other hand, OI proved effective at granting access to an international pool of young professionals with potentially novel perspectives. Overall, our findings suggest OI can be an effective tool for achieving *some* diversity policy goals, but it is not well-suited for achieving all stated aspects of diversity. Therefore, we suggest a more targeted approach to matching the opportunities for OI to achieve specific policy objectives.

1. Introduction

Diversity, equity, and inclusion (DEI) are increasingly being recognized as important policy goals for science, technology, engineering, and mathematics (STEM) organizations across the government and the industry, including space agencies such as NASA [1–3]. For instance, NASA identifies diversity and inclusion as a `a vital component of mission success´ [4]. There are both substantive and values-oriented rationales to this statement. First, from a substantive perspective, increased social diversity, often represented by demographic attributes, is documented to improve creativity and problem-solving, which in return increases organizational performance [5–7]. Additionally, diversity of work-related features, e.g., training, education, or tenure, provides organizations with a rich foundation of task relevant cognitive resources to draw from Refs. [8,9], enabling them to overcome `stubborn´ problems [10,11]. Furthermore, diversity of knowledge related features increases the absorptive capacity of organizations [12], rendering them more effective information users [13] that are more likely to innovate and survive in competitive markets [14–16]. Second, from a values-oriented perspective, reflecting the general fabric of the society within the workforce remains a vital inclusion objective for both national and international organizations [17]. Lack of diversity and inclusion in the upper-management and the rest of organizational

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processes [18,19] is documented to translate into bias and discrimination against underrepresented groups [20]. This mechanism leads to lower employee satisfaction, job related learning, and psychological safety [21]; and consequently, higher turnover rates [5]. Nevertheless, while more than 90% of federal STEM agencies recognize the promise of these benefits and report having an active diversity policy [1,2], progress is still insufficient [3], and there remains a significant underrepresentation of women, racial, and ethnic minorities [22]. The science and engineering workforce of NASA, like many other STEM organizations, remains predominantly male (76%) and Caucasian (75%) [23], with homogenous educational and employment backgrounds.

One approach that proponents argue could increase diversity among STEM innovators, is Open Innovation (OI). Broadly defined, OI involves broadcasting an organization's problem to potential `solvers´ outside the `seeker´ organization, for a chance to win a pre-defined prize [24–29]. The literature suggests that OI attracts a diverse pool of solvers from all backgrounds, who can employ their unique knowledge and perspectives to solve innovation problems [30–32]. From an engineering perspective, OI serves as a distant search mechanism [33] by enabling access to a wide-range of skills [34] and motivations [35–37] thus improving the problem-solving effectiveness of the seeker [38,39]. Furthermore, this strategy is thought to `engage new people and communities; build creative capacity´ [40]. As put by the current NASA Program Executive for Prizes and Challenges, OI can enable organizations to harness the perspectives, expertise, and enthusiasm of “the crowd” outside their walls to reduce costs, accelerate projects, enhance creativity, and better engage their stakeholders” [41].

The potential of OI has also been recognized by the US Government [42–44]. The America COMPETES Reauthorization Act in 2011 [45] aimed for, “granting all agencies broad authority to conduct prize competitions to spur innovation, solve tough problems, and advance their core missions”. In the decade since this reauthorization, federal agencies have launched close to 1000 prize competitions, ranging from public engagement activities (e.g., t-shirt design contests) to multimillion dollar engineering developments (e.g., US federal department of energy (DOE) offshore wind competition) [46–49]. Anecdotally, in addition to yielding some impressive technical successes, they have also brought new solvers to the table [50–52].

However, while the policy and academic literatures emphasize the potential for OI to reach diverse audiences, so far, there has been limited empirical evidence validating those propositions. Additionally, research on the intersection of DEI policy and OI has been unidirectionally conducted in isolation within their respective communities. For instance, OI literature investigated diversity to the extent that it serves the distant search mechanism [33]; thus, predominantly focused on knowledge distance related features such as expertise [53,54], educational background [55,56], and familiarity with a problem [32]. Even female representation within OI community came into attention as it relates to social marginality [34], and not for the purpose of DEI. From the other angle, management literature studied the influence of DEI related attributes on organizational performance, such as gender and demographics [18,19,21], knowledge [12–16], work related features [5–7], and skills and motivations [30–32]. Nonetheless, these studies did not specifically focus on DEI policy or considered OI as an instrument for supporting DEI policy objectives. In short, empirical work connecting diversified solver pools to the generation of innovative and useful solutions is still lacking.

This article aims to fill that research gap. One of the reasons for limited empirical evidence is the dearth of necessary data. The Paperwork Reduction Act [57] resulted in only data about winners being collected for most OI challenges, which greatly restricted the scope and richness of available information. This is a problem because agencies benefit from solutions through mechanisms such as gauging the state of the art, exploration of the design space, and reducing the resource burden; independent from solutions being the winner of a challenge or not [49]. Thus, understanding the ability of OI to attract diverse participants who could eventually provide valuable solutions, requires data on the full population of participants instead of just the winners. To gain insight into the population distribution, this work leverages a rich dataset that was generated through an OI field experiment that was previously conducted in collaboration with NASA [52]. The data at our disposal is unique because it tracks the population of potential participants along with their solving effort and solution outcomes, for a series of space robotics prize competitions. Moreover, these prizes mirror an internal development project at NASA, which allows for a direct comparison to the solution outcomes generated by `traditional´ solvers of similar problems, which are typically employed by STEM agencies. This allows us to distinguish the *registrants* of OI competitions (those who sign-up to learn more about the challenge and potentially solve), from the *quality solvers* (subset of registrants who provide conceptually complete and potentially useful solutions), and operationalize diversity in terms of both social and knowledge features.

Leveraging this unique data, we provide an initial empirical test of the implicit policy hypothesis that OI can contribute to STEM diversity goals without compromising on substantive technical solution improvements. While OI does indeed offer a path to attract diverse solvers who are capable of innovative contributions, our findings portray a more nuanced picture of what kinds of diversity can be achieved through this mechanism. Specifically, we found important variation in both the extent and direction of differences among the attributes of the OI population characteristics compared to NASA's. For example, the OI solving population included a different proportion of solvers who self-identified as female; however, the fraction of self-identified female solvers was even fewer than the predominantly male NASA population, which is the opposite direction from the DEI intent. On the other hand, in terms of providing access to young professionals and a diverse set of international and regional perspectives, OI provided sometimes significant improvements compared to the traditional employment mechanism. Importantly, not only was diversity observed among registrants, in most cases the same features of diversity were also reflected among the subset of registrants who provided high quality solutions. At the same time, many of these technical solutions outperformed the existing in-house solutions at NASA, while others provided novel engineering insights to difficult technical problems [52]. While the quality of the technical solutions is not the focus of this paper, it is a necessary condition for assessing both substantive and values-oriented policy objectives. Combined, these findings provide more nuanced insight into how OI can be more effectively tuned to serve multiple goals of space agencies such as NASA.

2. Literature review

2.1. Conceptualization of diversity in the literature

Diversity is defined as a unit level compositional construct that represents the degree of differences among the member of a unit with respect to a shared attribute [58]. Thus, it may refer to both (i) surface level features [59] that are immediately observable, such as biological sex or race; or (ii) deep-level features that describe underlying characteristics [60], such as knowledge and expertise. The similarities and differences in surface level features are easy to detect, and are important in a social context because they `evoke individual prejudice, biases or stereotypes´ [61]. On the other hand, deep-level diversity features are more intangible and may indicate values [62], personal traits [63], as well as attitudes, preferences and beliefs [60]. Due to their latent nature, these features are often expressed through behaviors, verbal and nonverbal communication, and personal information [64].

Despite the dichotomy of surface and deep-level diversity, the literature commonly adopts a *population level* conceptualization of diversity [65], that represents the position of a sample population along a homogeneity-heterogeneity continuum that are classified by one or more variables [66–70]. Furthermore, the literature broadly supports an understanding of diversity that is based on three monotonically increasing dimensions: variety, balance, and dissimilarity [71,72]. Thus, the term is quite flexible in terms of representing any characteristic of interest within a certain group boundary [73] and rich in terms of offering a variety of mechanisms for improvement, as indicated by the three dimensions.

2.2. Diversity in space policy

Within the space policy context, diversity is an important topic that has been primarily focused on the attribute-level. For example, the International Astronautical Federation (IAF) emphasizes what they term the `3Gs´, Geography, Generation, Gender [74]. This suggests an emphasis on individual attributes of surface-level features, where the goal is adding individuals that increase the value on a particular dimension; adding more women increases so-called gender diversity in a population that is typically male dominated. While NASA's statements on diversity also focus on surface-features, they are discussed at the level of the population. For instance, NASA's Office of Diversity and Equal Opportunity (ODEO) defines diversity as `the similarities and differences in the individual and organizational characteristics that shape our workplace´ [4]. This is emblematic of a population-level view of diversity, which focuses on matching attributes of the sample to the population from which it is drawn. The European Space Agency (ESA) also adopts a similar perspective; however, with an explicit focus on both surface and deep-level features. ESA's goal is [75] `to create a fully inclusive working environment where people value diversity in teams, take others' perspectives into account and feel comfortable being themselves – regardless of gender, gender identity and expression, age or working experience, sexual orientation, physical or mental challenges, ethnicity or educational, religious or social background´. This is consistent with the approach taken by many US federal STEM agencies [1] whose statements can be summarized as aiming to (1i) reflect the entire universe of US diversity in terms of gender, age, culture, education, talents & skills and (ii) to expand citizen participation by including all segments of society in terms of perspectives, characteristics, and life experiences [4,76–78].

All of these definitions adopt the values framing of diversity, implicitly assuming that it will lead to a more diverse knowledge base that would support performance outcomes. Moreover, while some of them call out specific features of diversity, they remain strategically vague about the relative importance or combinatorial impacts.

2.3. Approaches to measuring diversity

Given its broad relevance, numerous disciplines pursued to operationalize diversity, such as ecology [79–81], information science [82], economics [83,84], psychology [60,85], organization management [58,63,86], among others [87]. Consequently, there are a plethora of ideas regarding how to operationalize the concept and measure diversity. However, all of these approaches could be positioned within the Rao-Stirling framework, which characterizes diversity with three `necessary but individually insufficient properties´ of variety, balance, and dissimilarity [71,72]. While we do not intend to provide an exhaustive review, below we provide a high-level discussion of these properties along with some commonly used quantification methods.

The variety property simply captures the number of categories or levels the reference population is partitioned into, and is often captured by a simple count of elements [88]. The balance property represents the relative frequency with which these different groups are present within the population or the `evenness´ of the pool, which can be represented by the Gini Index [83], Shannon's evenness measure [89], or the Herfindahl Index [90]. Together, balance and variety properties are also known as the `dual concept diversity´ [91–93] and often used as a standalone measure. There are measures that jointly capture the dual concept diversity (both variety and balance properties), such as Shannon's Entropy [94,95] or Simpson Index [79]. These are utilized quite frequently within the innovation literature to quantify diversity of different population attributes, such as experience [96,97], knowledge [98–100], or demographics [15,101]. Finally, the dissimilarity property represents the degree of differences among the members of a unit [84,102]. Dissimilarity is often quantified through relatively more sophisticated network based approaches that measure the degree of relationships among the members of a population, such as betweenness centrality [103], dissimilarity matrices [93,104], network coherence [105] or distance measures [106]. To summarize, there are an abundance of perspectives to quantify diversity; however, not all of these approaches capture all three properties. Nonetheless, for the sake of completeness, it is useful to consider all three properties of variety, balance, and dissimilarity [72].

2.4. Open innovation as a diversifying mechanism

OI describes an approach to innovation where a seeking organization `broadcasts´ their problem to the `crowd´ for the promise of a pre-defined prize for the winning solutions [26–29]. Solvers in the crowd make their independent decisions to contribute solutions, if they wish, based on their expected stream of benefits and costs [27,29,33,107]. The broadcast mechanism has been theorized to produce novel and high-quality solutions because it enables solvers to bring their own perspectives to the problem-solving process [53,55,108,109]. This diversity in cognitive perspectives has been shown to lead to novel frame-breaking solutions that can overcome stubborn problems [32,33,51]. This type of search enables organizations to efficiently `reach´ solving perspectives that they would not otherwise have access to Refs. [33,110]. While the focus has primarily been on the knowledge distance of the solvers, some studies have identified social marginality as an additional productive dimension of distance [34]. This suggests that the broadcast mechanism might also be effective at eliciting contributions from non-traditional solvers who may face other barriers to participation.

However, another stream of the OI literature points out that widely broadcasted challenges tend to generate a large number of inappropriate solutions [37]. This can create a high evaluation burden for the seeking organization. One aspect of this `appropriateness´ problem is that distant solvers lack the institutional context to connect their proposed solutions to the specific needs and constraints of the seeker [111,112]. The other side of the picture is that the seeker may not have the shared knowledge basis to recognize the value in the distant solution [33,113]. Hence, there is an inherent information exchange barrier between the seeker and the solver that hinders effective communication of technical knowledge and associated risks; which leads to undesirable consequences when unaddressed [114]. This challenge of bridging across knowledge boundaries is well studied (c.f., [115,116]) and is only exacerbated when additional dimensions of diversity are introduced [37].

To summarize, although the potential for OI to reach diverse solvers has long been theorized, and public statements from multiple agencies have emphasized the potential for OI to serve DEI goals, so far, the empirical evidence connecting the two is limited. Additionally, embedded in these goals is the assumption that diversifying solvers would also support the Agency's innovation mission. Yet, the specific hypothesis that the broadening mechanism will also yield better solutions has not been tested directly. This lack of empirical testing has largely been due to a lack of data linking potential solvers to valuable solutions. Here, we address this gap by leveraging a unique data set that enables a direct comparison of the population reached through OI, to an internal workforce reference, while tracking the quality of the technical contributions of each group.

3. Materials & methods

3.1. Methodology – complementary procedures for quantifying diversity

Our objective is to empirically evaluate the efficacy of OI challenges to serve the DEI policy objectives of space agencies. Given the ambiguity in the concept of DEI in policy statements of diversity goals, we first outlined what DEI entails in § 2.1, then discussed what these constructs meant for STEM agencies in §2.2, and covered how diversity is `measured´ in the literature §2.3. As discussed in §2.1 diversity is a unit level compositional construct pertaining to a common attribute, hence warrants comparison of solver populations regarding a shared characteristic as a whole. Thus, our approach is to quantify diversity from multiple perspectives linked to attributes related to DEI policy and then compare the solver pools provided by an OI challenge against the benchmark internal workforce of NASA.

Recall from §2.3 that the literature broadly supports a view of diversity that is composed of three properties: dissimilarity, variety, and balance [71,72]. Therefore, we tailored our research method to probe each of these by implementing three mutually exclusive quantifications. Below, we describe each in detail.

First, to probe dissimilarity, one of the three properties of diversity as broadly accepted in the literature [71,72], we conducted Chi-squared tests to statistically evaluate if the reference solver datasets (registrants, quality solvers, and internal NASA reference) were statistically identically distributed or not. Here, it is important to note that while the Chi-squared test documents statistical difference and is therefore are an appropriate method to study dissimilarity, it does not capture the other two properties of diversity.

Second, we quantified variety and balance properties, also known as the standalone `dual concept diversity´ [91–93]. There are various mechanisms to operationalize this construct as discussed in §2.3. We implemented the two most popular approaches Shannon's Entropy and Simpson's Index. Shannon's entropy [80,94,117] is documented to be a robust general non-parametric approach for quantification of dual concept diversity (see Refs. [91,92] for a detailed discussion). It has been implemented in numerous management science studies to quantify diversity of experience [96,97], knowledge [100], domain expertise [99], and gender [15]. It is calculated following Eq. (1), where p_i is the proportion of the factor i in the measured category.

$$D_H = -\sum_i (p_i \log p_i) \tag{1}$$

We also implemented Simpson's index to provide additional support for dual concept diversity because of its seminal role in ecological diversity [118] and popularity in the management science literature. It has been used for quantifying diversity of knowledge [98], gender [119], and interdisciplinarity [120]. Simpson's measure is calculated following Eq. (2). In Eq. (2), n_i represents the value of abundance, N_t represents abundance that is $= \sum n_i$, and i represents the factors in the category.

$$D_s = \sum_i \frac{n_i(n_i - 1)}{N_t(N_t - 1)} \tag{2}$$

Finally, to understand the cross-section of DEI policy related attributes – we characterized the modal solver attributes for each solver population and discuss the similarities and differences among them. Modal characteristics are conveyed by the distributions and do not warrant computation; however, isolating them allows for an intuitive portrayal of the most common individual attributes that would emerge from each set. The purpose here is to draw out the combined effects of OI on the different dimensions of DEI. We computed the modal characteristic simply by calculating the mode of every diversity dimension (e.g., age, education level) individually, and then merged them to portray the modal solver characteristics in each set. Next, we discuss the unique dataset that enable this study.

3.2. Research setting and the data

The research question this article seeks to address is the efficacy of OI challenges to serve DEI policy objectives of STEM agencies while providing useful high quality solutions for complex interdisciplinary problems. Here the context, i.e., complex interdisciplinary STEM problems Space Agencies are interested in, differ from most OI prize competitions as they involve a high degree of interdependencies thus require deep knowledge and domain expertise in distinct disciplines, e.g., computer science and materials engineering, to be aggregated and applied in a specialized operational environment [121–125]. Consequently, numerous OI scholars argue it may be unlikely for crowd solvers to effectively solve such problems [50,126]. Thus, we required a rich dataset that provided: (i) the solver information about DEI policy relevant attributes discussed in Section 2.2; (ii) the detailed technical solutions they provided; and (iii) and the ability to compare the OI solver population to the workforce formed by the agency's internal employment mechanism.

For this purpose, we leveraged data from a previously conducted field experiment, the Astrobee Challenge Series, a prize competition that was organized in collaboration with NASA Center for Collaborative Excellence (CoECI) and Freelancer.com, one of the largest and most diverse open innovation platforms. The Challenge series sought solutions for a robotic manipulator design problem from a global crowd [52]. The data were suitable for the purpose of this study as it included not only the demographic (age, biological sex) and deep-level (education, experience, etc.) information of all solvers that participated in the challenge, but also provided the detailed technical solutions (including technical drawings, CAD and mathematical models, software modules etc.) of solvers who were able to complete the challenge and generate a solution. All solutions submitted to Freelancer.com were then analyzed by a group of NASA and the George Washington University research team experts in terms of their completeness and quality, to identify solutions that were conceptually complete.

Table 1
Diversity dimensions used in this study and their correspondence in the literature.

Variable	DEI Correspondence in Space Policy	DEI Correspondence in OI	Scale (all variables are categorical)
Biological Sex	Gender	Social Marginality	Male, Female, Prefer not to say
Age	Generation	Social Marginality	Under 18; 18–24; 25–34: 35–44; 45–54; 55–64; 65 & Up
Region of Residence	Geography	Social Marginality	East Asia & Pacific, Europe & Central Asia, Latin America & Caribbean, Middle East & North Africa, North America, South Asia, Sub-Saharan Africa
Education Level	Qualifications	Knowledge Distance	Below High school; High school; BSc; MSc; PhD
Years of Experience	Generation	Knowledge Distance	Under 5; 5–9; 10–14; 15–19; 20–24; 25–29; 30–34; 35–39; 40 or more
Number of Fields	Qualifications	Knowledge Distance	1, 2, 3, 4, 5, 6, 7 or more

Also, we obtained the reference internal solver population through the publicly available NASA (n = 10,743) and US robotics workforce[1] (n = 1,483,111) data [127–129].

For both the internal reference workforce of NASA and the crowd solver populations, we characterized diversity in six dimensions that relate to the previously discussed policy goals: biological sex, age, region of residence, education, years of experience, and number of professional fields the solver has experience in. These dimensions map to knowledge diversity and social marginality as broadly discussed in earlier sections and are commonly utilized in the DEI literature for operationalization. Moreover, we labeled the two subsets of the crowd solvers: (i) *the pool of registrants* and (ii) *the subset of solvers who submitted high-quality solutions (`quality solvers´).* Here, the registrants are all of the solvers that signed-up to solve an OI challenge (n = 9,215). Compared to the internal workforce, this subset corresponds to the capacity of the OI challenges to potentially reach a different solver population. On the other hand, the quality solvers (n = 85) are the subset of registrants that provided the solutions that were deemed to be of high quality (detailed or mixed detail per [52]) that can be potentially infused into practice or provide other benefits to the seeker (and hence could actually support DEI policy objectives of STEM agencies). Identifying both subsets supports our research objective of understanding the substantive and value-oriented potential of OI as a diversification mechanism. In Table 1, we summarize the diversity dimensions investigated in this study, their units of measurement, and correspondence within the Space Policy and OI literatures.

Before we proceed into findings, let us emphasize how the sequence of analyses discussed in Section 3.1 and the distinction between the three solver pools for the aforementioned DEI dimensions are necessary to address our research question. For OI to serve as a DEI policy instrument, first it should reach a more diverse solver population compared to the internal workforce of STEM agencies. However, this proposition is necessary but not a sufficient condition to address our research question. The necessary condition is that the reached diversity needs to be carried through the subset of solvers who are capable of providing value to the seeker, which are represented in our study with the quality solvers, and this pool also needs to be more diverse in comparison to the internal workforce. We may only argue that OI may serve as a tool for DEI policy if and only if both of these propositions are true.

[1] The region or residence information for the NASA workforce would not be reasonable because NASA has a requirement for its employees to be a US permanent resident. Thus, as a place holder, we used the US Robotics Workforce for this dimension of the internal workforce.

4. Findings

This section provides results for each of the analyses in turn. The overall insights are synthesized in the section that follows.

4.1. Visual inspection of solver pool characteristics

Given the unique nature of our data, we find it useful to initiate our discussion with a description inspection of the solver populations. Fig. 1, provides a visual representation of the distributions for each dimension studied across the three solver populations. Before reporting the results of the quantitative diversity analysis, we describe the overall trends to set the stage. Fig. 1A, portrays the distribution of biological sex, suggesting that the internal NASA workforce includes a significantly higher fraction of female solvers (~25%) compared to both solver sets provided by OI. We observe that the quality solvers include a much higher fraction of male solvers (>85%) compared to the registrants. Very few respondents selected `prefer not to say´, therefore, this category was not included in Fig. 1A.

Fig. 1B provides the age distributions, portraying that the NASA workforce is composed of a much more senior crowd, characterized with a left skew. We note that the registrants include a high fraction of young professionals with a right skew; however, the quality solvers exhibit a more balanced age distribution, and a higher contribution from middle aged solvers. Quality solvers also do not include any solvers that were under 18 or above 65 years of age.

Fig. 1C documents the distribution of region of residence; however, we would like to note that the internal reference here refers to the US robotics workforce and it excludes US citizens. The justification for not using the NASA workforce is as follows. All NASA civil servants are either US citizens or permanent residents. Thus, it is more instructive to look at the US robotics workforce and track their country of origin to see if the same global solver distribution is reflected among the registrants and the quality solvers. We observe that all three solver pools include a high fraction of South Asians; however, other than that they exhibit large differences in terms of the origin of solvers. For instance, the internal workforce portrays a skewed distribution, with few solvers from Middle East & North Africa and Sub-Saharan Africa. The registrant set is more balanced, with a higher contribution from Middle East & North Africa and Europe & Central Asia. The quality solvers include a higher contribution from Sub-Saharan Africa, Latin America & Caribbean, Europe & Central Asia; however, they include fewer solvers from Middle East & North Africa. To summarize, compared to the Asian dominated internal workforce, the quality solvers include an increased contribution from underrepresented regions in STEM workforce, with the exception of Middle East & North Africa.

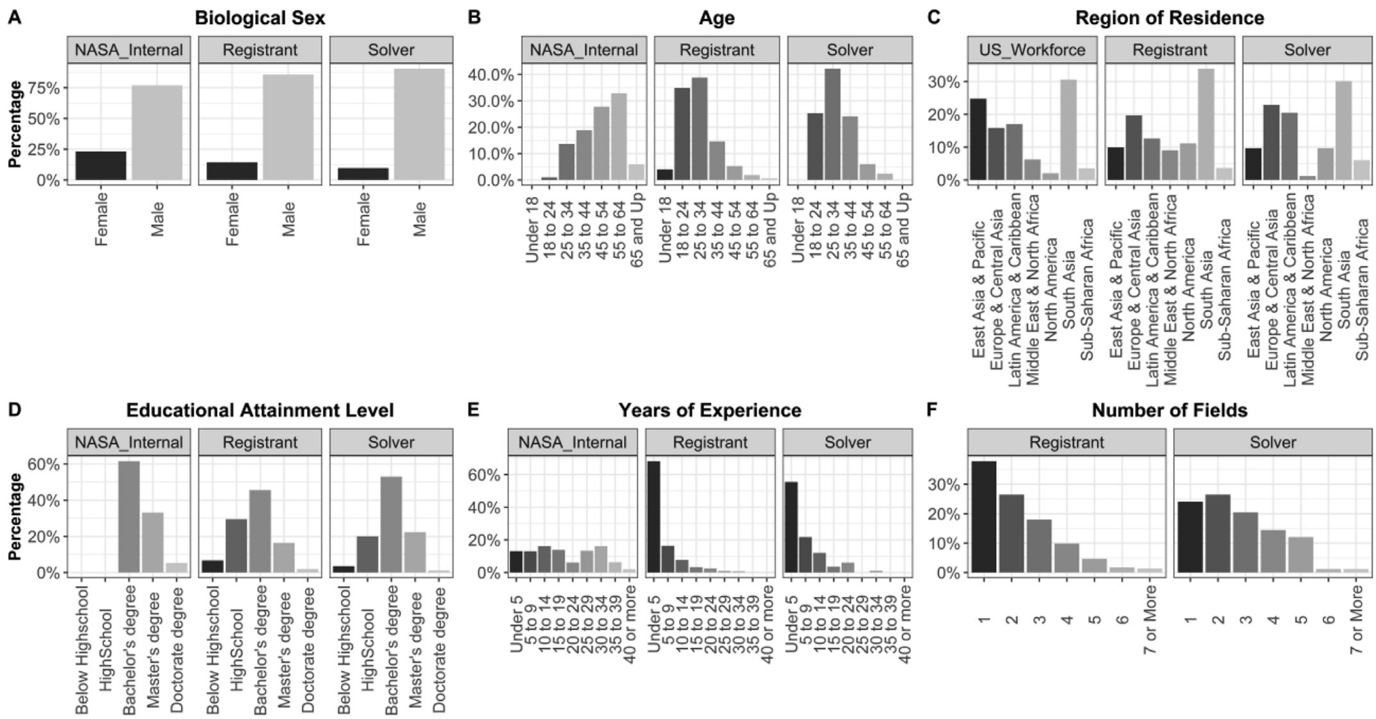

Fig. 1. Distribution of diversity dimensions.

Fig. 1D provides the distributions for educational attainment levels, indicating that the NASA workforce is mostly composed of BSc holders in addition to a sizable graduate group, led by over 30% MSc holders. The registrants and the quality solver pools indicate a more balanced distribution, with a concentration of less educated solvers including a considerable proportion of high school degree holders (~30%) and a small amount of below high school graduates. Interestingly, we would like to highlight that ~20% the quality solver population is composed of high school graduates, which is comparable to the proportion of MSc holders in this pool.

Fig. 1E provides the distributions for years of experience. In the case of the internal NASA workforce, we observe a considerably well-balanced group that is reminiscent of a uniform distribution. Registrants are composed of a strong concentration of young professionals, with roughly 65% that have less than 5 years of professional experience. Relatively speaking, although the subset of solvers that provide the useful solutions exhibit a more balanced distribution, it still contains a high concentration (~55%) of young professional compared to the internal workforce. Additionally, quality solvers include almost double the amount of well-seasoned professionals that have 20–24 years of experience.

Finally, Fig. 1F presents the distribution of the number of fields the solvers have professional experience in and only includes the pools of registrants and solvers due to lack of internal reference. Registrants are highly skewed to the right, with ~35% solvers who only has experience in a single field, followed by solvers with have experience in two fields (~25%). The quality solvers generally have experience in more fields characterized by a relatively balanced distribution and they are led by solvers who have experience in two fields with slightly over 25%. Additionally, quality solvers include roughly 50% more solvers with experience in four fields and almost double the fraction of solvers with experience in five fields. This may be a reflection of the trends observed in Fig. 1E. Neither of the sets includes a noteworthy fraction of solvers who has experience in more than five fields.

4.2. *Dissimilarity property of diversity — NASA vs. open innovation solvers*

In Section 2, we mentioned that diversity is as a population-level construct with three properties, one of which is dissimilarity. In our specific case, given the number of dimensions in the data and the difficulty of quantifying the degree of differences, we capture the dissimilarity property with Chi-Squared tests between the solver pools for each of the dimensions, and present the results in Table 2. A statistically significant result in Table 2 indicates that the two populations — Internal (i.e., NASA) and OI solvers (i.e., Registrants or Quality Solvers) — are statistically different from each other. This suggests that OI was able to attract a different body of solvers than those employed by NASA, for the specific dimension. In short, NASA employs a different composition of biological sex, age, region of residence, education attainment, work experience; compared to both the registrants and the quality solvers. The registrants and the quality solvers statistically differed in terms of number of experience fields ($p < 0.05$). Regarding age and region of residence, we found only weak evidence ($p < 0.1$) for statistical difference between the two OI pools. They were statistically homogenous in all other aspects.

While Table 2 documents that OI is capable of reaching a statistically different population of solvers, it is uncertain if this new solver pool is particularly more diverse in a way that is desirable from a policy perspective for the federal STEM agencies. Additionally, it is difficult to determine relatively how much OI contributes to diversity in each of these dimensions. Thus, we proceed to the quantification of variety and balance properties.

4.3. *Dual concept diversity — variety and balance properties — NASA vs. open innovation solvers*

Fig. 2 enables us to understand whether the Astrobee experiment was able to reach a higher variety and more evenly balanced set of solvers or not, which is an indicator of increased diversity. In

Table 2
χ^2 test of homogeneity between solver pools.

Diversity Facet	Registrants vs. Internal	Quality Solvers vs. Internal	Registrants vs. Quality Solvers
Biological Sex (df = 1)	$\chi^2 = 245.5$, $p < 2.2e-16$***	$\chi^2 = 8.4318$, $p = 0.0036$***	$\chi^2 = 1.4764$, $p = 0.2243$
Age (df = 6)	$\chi^2 = 9{,}504.5$, $p < 2.2e-16$***	$\chi^2 = 525.99$, $p < 2.2e-16$***	$\chi^2 = 11.51$, $p = 0.0738$*
Region of Residence (df = 4)	$\chi^2 = 4{,}720.7$, $p < 2.2e-16$***	$\chi^2 = 39.182$, $p = 6.592e-07$ ***	$\chi^2 = 11.864$, $p = 0.0651$*
Education Level (df = 4)	$\chi^2 = 1{,}425{,}536$, $p < 2.2e-16$***	$\chi^2 = 929{,}219$, $p < 2.2e-16$***	$\chi^2 = 6.8777$, $p = 0.1425$
Years of Experience (df = 8)	$\chi^2 = 7{,}931$, $p < 2.2e-16$***	$\chi^2 = 151.44$, $p < 2.2e-16$***	$\chi^2 = 10.52$, $p = 0.2304$
Number of Fields (df = 6)	NA[a]	NA[a]	$\chi^2 = 33.375$, $p = 0.0151$**

*p < 0.1, **p < 0.05, ***p < 0.01.
[a] Information was unavailable for NASA Solvers.

Fig. 2, the vertical black line set at 0% represents the diversity of the internal workforce, computed separately for each dimension using the two measures. The horizontal bars that are highlighted with colors represent the relative diversity value of the registrants and quality solvers, quantified by both Shannon's Entropy and Simpson's index. For the bar plots, a positive value greater than the baseline indicates an increased level of diversity (a more balanced distribution) compared to the internal population and a negative value indicates a decrease. We observe agreement between the two measures across the five dimensions. In terms of Biological Sex, Age, and Experience Diversity, Internal NASA workforce is more evenly distributed, implying that it is more diverse than the crowd attracted by the prize competition. Particularly for biological sex and years of experience, the difference is considerably large. In terms of Region of Residence and Educational Attainment Levels, both the registrants and the quality solvers are more diverse than the internal workforce. However, the difference is relatively small for region of residence and significantly large for educational attainment level.

When we compare the registrants to the quality solvers across the five dimensions, we observe that the quality solvers are almost always equal or less diverse, with a few exceptions. Quality solvers are more diverse than the registrants in terms of years of experience, roughly 10% of the baseline value; however, both are much less diverse than the internal reference. OI pools are comparable in terms of region of residence and age diversity. In terms of educational attainment level and biological sex, the registrants are visibly more diverse and the gap is around 10–15% of the baseline value.

4.4. The cross-section: modal solver characteristics for each pool — individual solvers as units of analysis

So far, our analysis focused on a population-level investigation of each diversity dimension. Nonetheless, all of these dimensions eventually lead to individuals who provide the design solutions, who may or may not support the DEI objectives due to their cross-sectional characteristics. Thus, we consider it useful to shift our unit of analysis, and compare and contrast the modal solver characteristics in each pool, because they provide a high-level summary of the most common individual solver attributes that emerge from the internal employment mechanism and the OI challenges.

The registrants and the solvers only differ in terms of the number of fields they have experience in, which changes from one to two. Though we don't have cross-sectional data about fields of experience for internal solvers, anecdotally, many NASA roboticists have experience in multiple fields assessed, suggesting that the potential trend from one (registrants) to two (quality solvers) would be sustained. Otherwise, external solvers exemplify a young professional from South Asia who has less than five years of professional experience and is within the age range of 25–34. The modal NASA solver exhibits a more seasoned profile, is between 55 and 64 years of age and has extensive, 30–34 years of professional experience, and is American by definition. Aside from that, the modal solver characteristics are identical for all three pools in terms of Biological Sex, and Education Level; portraying a male solver with a Bachelor's Degree. Table 3 portrays that the most common individual characteristics for the registrants and the solvers are

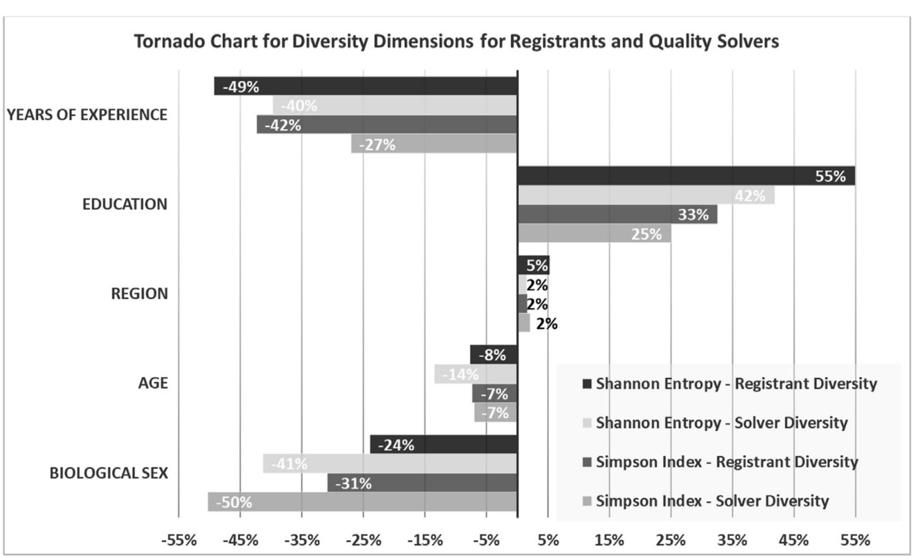

Fig. 2. Tornado plot for diversity dimensions.

almost identical and are reminiscent of a much younger, `fresh´ version of the aging solvers of NASA.

5. Implications for using OI as a diversifying mechanism

Having studied the diversity of the registrants and quality solvers in terms of particular attributes and population features, we now return to the question of the extent to which OI can serve as an effective diversifying mechanism.

At the highest level, we found that the population attracted through OI is statistically *different* than the internal professionals employed by STEM agencies in terms of features relevant to DEI policy. Moreover, the registrant population was largely similar to the quality solvers, with statistically significant differences only observed for number of fields (a knowledge feature, not specifically related to DEI). This suggests that the capacity for OI to attract diverse solvers translates to the subset capable of producing high quality solutions that can be potentially infused into practice.

However, the more nuanced question is whether the diversity that is achieved is supporting stated DEI policy objectives [4,74–78]. We adopted a population-level approach to investigate the efficacy of OI crowdsourcing mechanism to serve DEI policy outcomes on specific dimensions. Here, the results were mixed, with improvements in some dimensions and worse results in others. In terms biological sex, for which the policy goal is to increase the representation of females and other underrepresented gender identities in STEM, we found strong empirical evidence that OI, on its own, is not adequate to serve DEI policy objective of reducing male overrepresentation (i.e., reducing the fraction). In fact, our data reveal the opposite trend. Both the registrants and the quality solvers include a considerably higher fraction of male solvers compared to the already imbalanced solver pool of NASA. While our study is not suited to provide a causal explanation to the observed gender gap, it could be attributed to a variety of social and psychological mechanisms that originate from gender differences and their nuanced implications on preferences of individuals towards different decision situations [130]. Relatively speaking, compared to women, men are documented to be more stimulated by competitive challenges, arguably because of their socialization [131]. Furthermore, as observed in controlled experiments, men have a tendency to be overconfident in their relative performance and probability of success when faced with uncertain tournament entry decisions [132]. Collectively, these factors might be positively influencing their decision to participate in prize competitions due to the self-selection mechanism. Nonetheless, this finding highlights the importance of matching the policy mechanism to the goal. It is also worth noting that other non-competitive implementations of OI that focus on collaborative communities have been more successful at increasing participation by underrepresented groups [133].

Regarding age, experience, and education diversity, the policy objective is to obtain a more evenly distributed pool with the goal of representing more perspectives in the workforce. Particularly in the space industry, there is an additional goal of attracting younger solvers, due to fears of a `demographic cliff´ causing knowledge and skill gaps, hindering the innovation potential of organizations [134–136]. These objectives were achieved to some extent. We found that a much younger, `fresh´ solver pool is attracted by OI; however, where internal solvers are thought to be too concentrated in the 50+ age range, the OI solvers are even more concentrated, albeit with people aged 18–35 with under 5 years of professional experience. While the younger part of this demographic is well represented in the registrant pool, they are less likely to provide valuable solutions. This suggests that recruiting much younger solvers may not translate to innovative results, even if they could bring different perspectives. Moreover, the core value of diverse perspectives in the solving process is not achieved if OI is only attracting a narrow slice of the demographic range.

In terms of regional perspectives, where the DEI policy goal is to expand citizen participation and reflect the overall composition of the public [3,4,74,75] we found that OI is quite effective. Both the crowd and the solver pool include a large fraction of solvers from all around the world. While the specific regional distribution was not exactly representative of the U.S. demographics, we found an increased representation of historically underrepresented communities in STEM, which could support the much needed access for diversity. This can be particularly important for international space organizations seeking `geography´ diversity since we found evidence of much more innovative capacity than anticipated in regions currently underrepresented in the industry. This finding is less directly relevant to domestic DEI policies; however, it suggests the potential power of OI tools to reach previously unrecognized talent. This is especially true since the same types of geographic diversity were also represented among quality solvers.

Overall, these findings add significant confidence to the potential for OI to serve as a diversifying tool. Nevertheless, they also highlight the importance of carefully targeting the tool to the specific policy objective. OI effectively overcomes certain workforce barriers, by enabling ad hoc skill-based engagements rather than career hiring. This makes it feasible to dynamically match particular skillsets to problems. As a result, a junior solver with a narrow (but highly relevant) skill set may be more able to compete for the specific prize competition but not the more generally defined employment opportunity. This creates more opportunities for people with less traditional backgrounds to gain access. Yet, because of short term, at-risk nature of a prize competition (many participants leave with no reward) this format can keep away otherwise capable solvers, and is particularly relevant to some of the demographics that DEI policies aim to reach. Therefore, when used in its open-broadcast format, it is important to realize that OI is more tuned to two of the 3 Gs (i.e. geography and generation, but not gender).

Within the framework of OI, advances in theory related to prize design make it possible to support other aspects of diversity. For

Table 3
Model solver characteristics.

Diversity Facet	Internal	Registrants	Quality Solvers
Gender	Male	Male	Male
Age	55–64	25–34	25–34
Region of Residence	US Person[a]	South Asia	South Asia
Education Level	Bachelor's Degree	Bachelor's Degree	Bachelor's Degree
Years of Experience	30–34	Under 5	Under 5
Number of Fields	NA[b]	1	2

[a] NASA civil servants are US persons by definition.
[b] Number of fields solvers have experience in variable was unavailable for NASA Solvers.

example, when formulating a prize competition, seekers must consider multiple aspects including: (i) which channels to use for broadcasting; (ii) how the framing of the technical problem can attract different types of solvers; and (iii) the ways that seekers, and other partners, engage with the solvers throughout their solving process. Although arms-length prize-competitions are still the most popular format for OI, there are significant benefits to formats that leverage more continuous engagement over the course of the competition. Recent work has documented the full range of benefits that accrue through repeat interactions with multiple stakeholders even in the context of a completion [49]. These longer-term challenge formats make it feasible to lower the risk and competitiveness barriers for participants, while preserving many of the diversifying aspects. NASA's centennial challenges program, for example, has created pathways for solvers with non-traditional backgrounds to join projects based their demonstrated capabilities in the competitions [137].

These findings also shed light on the tradeoff between broadcasting as widely as possible and specifically targeting potentially valuable solvers. So far, this has been framed in terms of whether it is possible to predict: (i) the source of potential frame-breaking solutions in advance; and (ii) the risk of being overwhelmed by inappropriate solutions. In the context of OI for DEI, the dimensions of diversity one wishes to attract is certainly known a priori, while the need to reduce barriers due to competition and risk can be important stochastic factors to consider during problem formulation [138]. This suggests the value of designing challenges with diversity in mind. Our results point to some of the critical dimensions for doing this.

6. Conclusion

While the literature broadly agrees that increasing diversity in the STEM workforce will lead to better outcomes [6,7,9,12,14,20], organizational efforts to meet this objective have been largely unsuccessful [3]. According to its proponents, the rising popularity of OI methods among the STEM agencies [44,48] brings forth a potential remedy to this issue, with the claimed ability of creating more equal opportunities for participation by reducing the barriers to access [48,139,140]. The core argument is that, by opening institutional problems to anyone with a solution [141], the bias in assumptions regarding the profile of potential solvers will be eliminated [27,108], which should eventually lead to a solver pool that is more representative of the general fabric of society [142,143]. Although these arguments have been used by many to encourage wide-spread adoption of OI, so far, the connection between OI and diversity and the proclaimed substantive benefits have not been empirically established. To that end, this article provided a first empirical test of the ability of OI to contribute to the diversity, equity, and inclusions policy goals of STEM agencies such as NASA, by generating valuable design solutions from diverse populations.

We found strong support for the capacity of OI to attract a contrasting pool of solvers compared to the internal workforce employed by STEM agencies. However, the ability of this new pool to address DEI policy objectives is not consistent across all relevant dimensions. In particular, inclusion of female solvers was even worse in the OI population compared to the internal workforce. On the other hand, inclusion of both generation-based and geography-based differences benefited from the broadcast mechanism. We saw many younger solvers in the OI population, but that youth was strongly concentrated between ages 18–35, which can introduce its own challenges. Geographical diversity saw the most useful improvement, with solvers from underrepresented regions providing some of the highest quality solutions. Finally, while this study drew on data from only one challenge series, we believe that the main findings generalize. This specific robotics problem was selected because it represents a highly technical area where we might predict that the expected solver profile (robotics experience) would be particularly important. Therefore, if anything, these results should be conservative in terms of the diversifying potential of the crowdsourcing mechanism. Further research should be conducted to replicate these findings in other areas to deepen the insights regarding the potential benefits and limitations.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Taylan G. Topcu reports financial support was provided by National Science Foundation. Zoe Szajnfarber reports financial support was provided by National Science Foundation.

Data availability

Data will be made available on request.

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