Crowd Equals Diversity? A Diversity Analysis on Participation of Agency-sponsored Open Innovation Challenges

By
Lihui (Lydia) Zhang
B.A., Smith College, 2018

Submitted to the Institute for Data, Systems, and Society in partial fulfillment of the requirements for the degree of Master of Science in Technology and Policy at the MASSACHUSETTS INSTITUTE OF TECHNOLOGY
February 2021
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Abstract

Recent events in the US and beyond have stirred societal debates on how to measure and increase diversity in fields such as Science, Technology, Engineering, and Math (STEM). In the past decade, many US public agencies with STEM missions have explored crowd-sourced, open innovation challenges as a potential solution. To probe whether and how diversity has been achieved in this context, this thesis addresses three goals: (i) understanding the multi-faceted nature of diversity and its determinants based on literature review across disciplines, (ii) testing whether open innovation challenges achieve the policy objective of increasing diversity in solvers for public agencies, and (iii) investigating whether increased diversity leads to desired innovation outcomes.

This thesis leverages the NASA-Freelancer Astrobee Challenge Series (ACS), an online robotics design prize competition, as a case study. Through a systematic literature review, this thesis proposes a multi-dimensional diversity definition, covering surface vs. deep, absolute vs. relative, and individual vs. population diversity perspectives. It adopts a mixed approach of inductive coding and natural language processing to extract motivation from solvers; one-way ANOVA and Tukey test to examine the significance between diversity and solution quality generated in ACS.

The study finds that ACS, a representative of open innovation challenges, does not generate all dimensions of diversity in its solvers. On the surface-level dimension of diversity, we observe that ACS achieves greater inclusion in some features such as age and country, but not so much on gender. ACS also achieves some extents of deep-level diversity, reflected in features such as education, career backgrounds, and motivation. Furthermore, insights from the study show that achieving diversity of solvers in certain features does not necessarily lead to quality solutions.

Based on these insights, this thesis formulates a series of policy implications for STEM federal agencies, exploring the effectiveness of open innovation challenges as a policy mechanism for increasing diversity. It also generates suggestions to improve solution quality of future open innovation challenges.

Thesis Supervisors: Zoe Szajnfarber, Dava J. Newman
Title: Professor and Chair of Engineering Management and Systems Engineering at the George Washington University; Apollo Professor of Aeronautics and Astronautics
Acknowledgments

This thesis is a special milestone, documenting a period of my life that is defined by curiosity, challenges, perseverance, and rewards. I would not ask for anything more or less than what has happened. I am grateful for this Institute for taking me in and allowing me to grow the way I did. Of course, this journey would not be possible without the support from my dear advisor Prof. Zoe Szajnfarber, who nurtured me both as a researcher and a person tremendously in the past two and a half years. Thank you for your patience in repeating, persuading and encouraging on my every little step until this finish line. Thank you, Dr. Taylan Topcu and the rest of SzajnLab teammates, who kindly shared their time and wisdom, guiding me through the ups and downs in research and always encouraging me to keep going. Thank you, Prof. Dava J. Newman, for your inspirational presence and teaching. Thank you, Prof. Olivier L., de Weck for trusting in me.

My extended family at the Technology Policy Program, Professor Frank Field, Professor Noelle Selin, "Barb" Ms. Barbara DeLaBarre, and "Ed" Mr. Ed Ballo for making this experience one of a life time. I would not be where I am today without my friends and family who always present despite our great distances. My fellow TPP friends, and among whom, Maryam Shahid, Karan Bhuwalka, Nicolas Zhang, Gabriel “Gabc” Bann, Becca Browder, thanks for being my anchors and inspirations. Danwei “Jenny” Huang, Yuxin “Megan” Fu, Quizi “Chelsey” Chen, Qiansha “Karina” Huang, Himani Mehta, Maya Nasr, and many more, your presence made Boston another hometown. I am so grateful to have shared life with you.

Last but not the least, my dearest families, my parents, to whom this language might not make the most sense but nevertheless deserve the most of my recognition. This work is dedicated to you, for your unconditional love and support, for trusting in my vision and dreams even when I dither.

To the next chapter, come sail away.

This research is supported by NSF Grant: CMMI-1535539.
Executive Summary

Recent events in the U.S. and beyond have focused the social attention on the complicated issues surrounding diversity and inclusion, with debates on how to measure and increase diversity, particularly in fields relevant to Science, Technology, Engineering, and Math (STEM). Many U.S. public agencies with STEM missions have recognized this issue and explored ways to increase diversity in their respective domains. One such approach is to launch crowd-sourced, open innovation challenges, under the broad assumption that they are an effective strategy to attract diverse solvers. However, there is an ambiguity regarding what constitutes diversity, and a lack of empirical evidence about whether diversity is being achieved through the mechanism of open innovation challenges. Given this research gap, this thesis addresses three goals: (i) understanding the multi-faceted nature of diversity and its determinants based on a comprehensive literature review, (ii) testing whether open innovation challenges achieve the policy objective of increasing diversity for government agencies, and (iii) investigating whether increased diversity leads to desired innovation outcomes.

To that end, this thesis leverages the NASA-Freelancer Astrobot Challenge Series (ACS), a robotics design competition to support the International Space Station, as a case study. This unique field experiment offers a fitting context to study a crowd of 9000+ who participated in a STEM space robotics challenge. The data includes detailed demographic and motivational information of the participants, along with their submitted technical designs. To link this data with the research question on diversity, I conduct a systematic literature review on how the construct of diversity is defined across disciplines, and assemble a multi-dimensional definition to capture its nuanced nature. The definition considers diversity from surface vs. deep, absolute vs. relative, and individual vs. population perspectives. To extract deep-level information of motivation, I formulate a mixed method approach that integrates qualitative approaches with natural language processing. I then use the proposed definition, and the motivational information, to investigate whether open innovation approaches, such as ACS, achieve NASA’s policy goals for diversity and lead to quality solutions.

The study finds that ACS, as a representative of open innovation challenges, does not achieve all types of diversity, in terms of diversity dimension or feature, all the time. Our findings reveal that an important policy objective is unmet as ACS is not effective in attracting more females into solving STEM problems. Despite so, ACS achieves a more diverse population than the internal solvers who are tasked the same problems in other attributes, such as age, country, work experience, and education.
level. Specifically, the ACS crowd is more diverse because they are: younger, representing more countries, with more and different work experience (including non-STEM expertise,) and having different education attainment levels, when compared to the internal solvers.

It is also found that the more diverse solvers identified in ACS are not equally responsible for generating productive innovation. For example, while open innovation attracts a younger population, only Generation Y has a higher probability of generating quality solutions. People with a bachelor's degree and above, and foreign (non-U.S.) contestants are also more likely to generate productive innovation. Furthermore, findings show that the most underrepresented motivations (“self-starter” and “extrinsic”) identified from the solvers are the most productive motivations in generating quality solutions.

Based on these insights, I discuss the policy implications for STEM federal agencies, exploring the effectiveness of using open innovation as a policy mechanism for increasing diversity, as well as generating suggestions to improve solution quality of future open innovation challenges.
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Chapter 1 Introduction

“Government should be collaborative. Collaboration actively engages Americans in the work of their Government. Executive departments and agencies should use innovative tools, methods, and systems to cooperate among themselves, across all levels of Government, and with nonprofit organizations, businesses, and individuals in the private sector.”

— Former President Barack Obama, on his first day as President [1].

In the past two decades, over a hundred U.S. federal agencies have extensively exploited prize challenges as a source of innovation and a channel for diverse participation in solving tough problems in their respective domains. Prize challenges offer monetary and non-monetary benefits to incentivize participation in order to achieve scientific and technological innovation from the public, or the "crowd" [2]. Some famous examples include the Google Lunar X-Prize [3], IBM Watson AI X-Prize [4], and the Netflix Prize [5]. Examples sponsored by federal agencies include the NASA Centennial Challenges Programs and their various space-themed challenges, such as the 3D Printed Habitat Challenges, Space Robotics Challenges and the Cube Quest Challenges [6], the National Institute of Health (NIH) and their Brest Cancer Startup Challenge and Wearable Alcohol Biosensor Challenge [7]. The U.S. General Services Administration has operated Challenge.gov as an online resource hub to support and manage over 1000 public-sponsored prize competitions since 2010 to present. See Figure 1.1 [8]. The total amount of prize money offered by these federal prize competitions has increased over time. As shown in Figure 1.2, the total prize amount rose from $247,000 in Fiscal Year 2011 to $37 million in Fiscal Year 2018, with a median prize money per competition raised from $34,500 in FY2011 to $80,000 in FY2018 [2], [8].
Pieces of legislations, policies and congressional authorization have paved the way for the rising popularity of public prize challenges. The 2009 *Strategy for American Innovation* is a national strategy launched by the Obama Administrations, led by the National Economic Council, Council of Economic Advisers, and Office of Science and Technology Policy. It aims to strengthen America’s capacity to innovate. It details how “the Administration, the American people, and American businesses can work together to strengthen a long-run economic growth," one that is essentially based on innovation [9], [10]. This national strategy encouraged public agencies to start exploring the broad concept of open innovation, by conducting a variety of initiatives that “motivate solvers participate to improve, secure, and enhance missions of Federal agencies,” such as citizen science, collaborative ideation, hackathon, code-sharing [11]. The reauthorization of the *America COMPETES Act* in 2011 provided clear legal guidance for federal agencies to use appropriated funds towards challenge and prize competition. It authorized the head of federal agencies to launch prize competitions that "have the potential to stimulate innovation and advance agency’s mission" [2]. The passage of the *American Innovation and Competitiveness Act* in 2017 expanded the authority of federal agencies to partner with private sector, for-profit and nonprofit entities to conduct cash and non-cash prize competition.[12]

In more recent years, the ‘Trump administrations’ has continued to support efforts by federal agencies to host prizes and challenges, as exemplified by the series of federal sponsored prize challenges on developing solutions for COVID-19 [13][14].

In parallel with the rising popularity of open innovation among U.S. federal agencies, is the rising discussion on the lack of diversity in fields of Science, Technology, Engineering, and Math (STEM.) Such discussion centers around the under-representation of minorities in gender, race, ethnicity and other societal factors due to bias in the STEM fields, resulting in a mismatch between
the composition of the STEM population and that of the U.S population. More than 90% of federal agencies report to have an active management of diversity [15], [16]. However, despite their efforts, the improvement of diverse workforce in federal agencies is still reported to be rather insignificant [17]. There is still a widely observed underrepresentation of women, racial and ethnic minorities in the U.S science and engineering labor force [18].

In a STEM-related federal agency such as NASA, which is the reference organization in this thesis, diversity and inclusion has been recognized as "vital components of mission success"[19]. 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" [19]. In a recent publication, ODEO revealed that the racial composition of NASA workforce is 72% Caucasian, 12% African American, 7% Asian American or Pacific Islander, 8% Hispanic or Latino; 1% American Indian or Alaska Native, and less than 1% are more than one race [20]. Among the NASA workforce, 65.7% are males while 32.3% are females. As a comparison, the US national civilian labor force composes of 51.8% males and 48.2% females [21]. Figure 1.3 represents comparison of NASA workforce and national civilian labor force by race, ethnicity and gender.

Figure 1.3 Comparison between NASA workforce and US national civilian labor force by race, ethnicity[19] and gender [21]
1.1 Problem Statement & Research Questions

Facing pressure on achieving diversity in STEM fields and acquiring innovative solutions, federal agencies have proposed open innovation initiatives (e.g. prize challenges) as a potential partial remedy. Many STEM federal agencies justify their use of prize challenges through its suggested multifaceted benefits in generating innovative solutions as well as reaching a diverse community from the crowd [22]–[24].

While these initiatives have gained popularity under the broad assumption of realizing both innovation and diversity, the calls and definition for diversity by federal agencies have been rather unclear [25]–[27]. In addition, there has been a dearth of study relating the diversity of solvers to the effectiveness of prize challenges, judged by the innovation outcomes, partly because of a lack of suited data. This has left federal agencies that sponsor and manage such initiatives uncertain about whether prize challenges are indeed generating the desired impacts in innovation and diversity.

Armed with a unique empirical dataset on a federal prize challenge, this thesis pursues two research questions that are structured to understand the impact of open innovation policy decisions on diversity in STEM fields.

RQ.1. Given the policy objective of increasing diversity in STEM fields, to what extent have federal prize competitions reached a more diverse population of solvers than their internal workforce?

To address this research question, we first propose a multidimensional diversity definition, through a literature review across disciplines. The included dimensions are aligned with the agency policy goals on diversity, including perspectives from absolute vs. relative diversity, individual vs. population diversity and surface vs deep-level diversity. Then, we leverage a unique field experiment, the NASA-sponsored Astrobotic Challenge Series (ACS) and investigate whether the crowd is more diverse compared to the demographics of the NASA workforce [28]. This high-fidelity comparison enabled by the unique ACS data allows me to probe into the effectiveness of open innovation challenges in terms of addressing diversity policy objectives of STEM agencies.
RQ.2. To what extent, if at all, has achieving increased diversity led to innovative solutions?

A natural follow up on RQ.1 is to ask if increased diversity leads to improved innovation outcomes. Some scholars have studied the relation between solution quality and certain diversity aspects, such as knowledge diversity and motivation [29], [30]. However, previous work has primarily focused on facets of diversity rather than its complex and multidimensional nature. Therefore, it is unclear if (or which dimensions of) diversity leads to improved innovation outcomes. RQ2 is formulated to understand the nuanced relations between diversity and innovation outcomes in a prize challenge.

1.2 Structure of the Thesis

The thesis starts with literature review in Chapter 2 on the definition of diversity across disciplines, and proposes a multi-dimensional definition that captures its nuanced nature from multiple perspectives. In addition, Chapter 2 includes the status quo demographics of NASA and the US robotics workforce, the policy intents on diversity by federal agencies and organizations alike, as well as crowds’ motivations in participating such challenges. Chapter 3 introduces the unique dataset of ACS and different measures that enable the diversity analysis on a complex technical open innovation challenge. Chapter 4 presents the results of our exploration of the research questions. Chapter 5 discusses the insights on achieving diversity through open innovation challenges and their policy implications.
Chapter 2 Literature Review

This thesis focuses on the interplay between diversity and open innovation. Therefore, we start with a systematic literature review on the two concepts. This section probes into what diversity is, including the various angles of defining and measuring diversity as a societal construct. It then delves into the studies on open innovation and crowd sourcing, from both the organization’s and solver’s perspectives. Combining these two perspectives provides a more holistic understanding of what diversity means across different disciplines and stakeholders.

2.1 What is Diversity?

A general definition for diversity is that it examines the variety of differences within a certain group boundary [31]. When it comes to measuring the diversity of a social unit, given the unlimited characteristics and features associated with any given individual within that unit, the measurement of differences hence increases in multidimensionality and require dissections before any conclusions can be drawn. Therefore, diversity is a complex social concept and it is “multidimensional” [32].

As a complex concept, diversity is both a structure and a content [32]. According to Jackson et al., although diversity does not exist on an individual level, it is based on the collective analysis of individuals. In other words, individual attributes make up the content of diversity, and the configuration of these attributes in a social unit makes up the structure of diversity [32].

As a multidimensional concept, diversity evolves across organizational boundaries and emerges through different attributes of individuals. It’s essentially any way that any group of people can differ significantly from another, be it in appearance, sexual orientation, veteran status, role in the organization, and so on [33].

In the following subsections, we start with an overview on the current definitions of diversity by STEM federal agencies and identify the issue of their inconsistency. To address this, we then propose a definition that considers diversity from three dimensions: surface vs. deep-level diversity, absolute vs. relative diversity, and population vs. individual diversity. Each dimension pair introduces a perspective to understand and define diversity. Briefly, the justification for selecting these three dimensions is as follows. We choose to discuss surface and deep-level diversity because it is a widely
adopted theoretical framework in examining the content of diversity, particularly by studying attributes of individuals. We choose absolute and relative diversity because this comparison presents alternative views on the structure of diversity. And lastly, population and individual diversity offer two different perspectives to think about diversity: top-down (population) vs. bottom-up (individual).

2.1.1 How do STEM Federal Agencies Define Diversity?

While most agencies reportedly have an active management of diversity [15], [16], a review on their departmental diversity and inclusion policy statements suggests a rather unclear and inconsistent definition of diversity within and across these agencies.

We select a group of federal agencies to study their definitions of diversity via various sources, including diversity and inclusion strategic implementation plans, official websites of the diversity and inclusion offices, press releases, and so on. These five agencies all have STEM missions, and they are the sponsors of a National Academy of Science study on The Role of Inducement Prizes [34], making them active adopters of federal prize challenges. They are: National Aeronautics and Space Administration, National Science Foundation, Department of Energy, Department of Health and Human Services, and National Institute of Standards and Technology. Table 2.1 below shows the various definitions and goals on diversity by these agencies.

Table 2.1 Selected STEM Federal Agencies and Their Definitions and Goals on Diversity

<table>
<thead>
<tr>
<th>Selected STEM Federal Agencies</th>
<th>Agency Definition and Goals of Diversity</th>
</tr>
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<tbody>
<tr>
<td>National Aeronautics and Space Administration (NASA)</td>
<td>At NASA, we define diversity <strong>broadly as the entire universe of differences and similarities</strong>[25]. Diversity is the similarities and differences in the individual and organizational characteristics that shape our workplace…NASA needs to be reflective of the diversity of America at all levels of the organization[35]. Diversity is defined as the <strong>unique characteristics, perspectives and life experience</strong> that define us as <strong>individuals</strong>[36]. If we want to ensure our workforce reflects the diversity of the public we serve, we need <strong>individuals from a wide variety of backgrounds, skills, and abilities that can bring unique perspectives, and life experiences</strong>, to tackle highly complex challenges to achieve NASA’s mission.</td>
</tr>
<tr>
<td>Selected STEM Federal Agencies</td>
<td>Agency Definition and Goals of Diversity</td>
</tr>
<tr>
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</tr>
<tr>
<td>National Aeronautics and Space Administration (NASA)</td>
<td>(Cont’d) NASA’s Special Emphasis Programs (SEP) focus special attention on groups that are conspicuously absent or underrepresented in a specific occupational category or grade level in the agency’s workforce. These efforts focus on nine critical segments of our workforce: African American; American Indian/Alaska Native; Asian American/Pacific Islander; Hispanic/Latino; Individuals with Disabilities; Lesbian, Gay, Bisexual, Transgender &amp; Allies; Veterans; Women; Young Professionals. [37] [38]</td>
</tr>
<tr>
<td>National Science Foundation (NSF)</td>
<td>NSF’s goal in workforce diversity is to recruit from a diverse, qualified group of potential applicants to secure a high-performing workforce drawn from all segments of society. [39] Workforce diversity is defined as a collection of individual attributes that together help agencies pursue organizational objectives efficiently and effectively. These include, but are not limited to, characteristics such as national origin, language, race, color, disability, ethnicity, gender, age, religion, sexual orientation, gender identity, socioeconomic status, veteran status, educational background, and family structures. The concept also encompasses differences among people concerning where they are from and where they have lived and their differences of thought and life experiences.[40] NSF programs are available to increase the participation of individuals from underrepresented groups in all levels of the STEM educational system and workforce… such as Alaska Natives, Native Americans, Blacks or African Americans, Hispanics, Native Hawaiians and other Pacific Islanders, and Persons with Disabilities. It should be noted that, among the many fields of STEM, identification of a particular group as underrepresented may vary by discipline (e.g., women are underrepresented in some fields). [41]</td>
</tr>
<tr>
<td>Department of Energy (DOE)</td>
<td>There is no single, universally-accepted definition of “diversity” or “inclusion” [27]. […] Diversity describes an environment where the talents and differences of all employees are respected and valued for professional and mission success. At DOE, as a science and technology agency, we have unique diversity characteristics that must be addressed. This includes the broad spectrum of characteristics including, but not limited to, race, color, ethnicity, national origin, gender, age, religion, culture, language, disability, sexual orientation, gender identity, socioeconomic status, family structures, geographic differences, diversity of thought, technical expertise, and life experiences [27]. […] DOE shall recruit and hire from a diverse, qualified group of potential applicants to secure a high-performing workforce drawn from all segments of American society[27].</td>
</tr>
<tr>
<td>U.S. Department of Health and Human Services (HHS)</td>
<td>We define diversity as all the ways in which people differ, including innate characteristics (such as age, race, gender, national origin, mental or physical abilities and sexual orientation) and acquired characteristics (such as education, socioeconomic status, religion, work experience, language skills, cultural values, geographic location, family status, organizational level, work style, philosophical and intellectual perspectives, etc)[42]. […] Special Emphasis Programs (at HHS) are management programs established to ensure equal employment opportunity for minorities, women, veterans and persons with disabilities in various categories and occupations, and in all organizational components throughout the Department[43] […] The Special Emphasis (identified in FY 2016) are: people of Hispanic origin and individuals with disabilities [44]</td>
</tr>
<tr>
<td>National Institute of Standards and Technology (NIST)</td>
<td>NIST continually strives to establish and maintain a workforce that reflects America’s diverse populace and promotes an environment that respects and values individual differences. NIST recognizes that the ability to recruit, develop, and retain a highly skilled and diverse workforce is key to the Institute’s continued success [45].</td>
</tr>
</tbody>
</table>
As shown above, the current definitions on diversity are not consistent and clear within and across federal agencies. Some agencies have rather broad definitions on diversity (i.e., “Diversity is the similarities and differences in the individual and organizational characteristics that shape our workplace [35]) while others provide a list of characteristics that form diversity without in-depth explanations on their relations, and justification for such selections (i.e., see rows of NSF and DOE.) Furthermore, within the current definitions among agencies, there is a lack of specified guidance on how to reach, measure, and enhance each of the diversity target. For example, by saying “we have unique diversity characteristics that must be addressed including, but not limited to, race, color […]” [27], it is unclear as how each of these characteristics should be addressed - whether judged by its quantity, proportion or comparison to other criteria. These unclear definitions and objectives of diversity pose a challenge to quantitatively measure and benchmark the diversity performance of open innovation initiatives, such as a prize challenge in our case, to the stated departmental diversity goals. To take a step towards this goal, the following sections define diversity from various perspectives and propose respective measurements, in an effort to better capture the nuance of this social construct.

2.1.2 Surface vs. Deep-level Diversity

Two theoretical concepts are prominent in the categorizations of diversity: (1) surface diversity that describes the “readily detectable attributes (of people)” (2) and deep-level diversity that defines the “underlying attributes” [32], [46].

Harrison et al. defines surface diversity as easily observable demographics characteristics, such as age, gender, ethnic/race, national origin, etc. [46], [47]. The similarities and differences in these features while are easy to detect, and are important in a social context because they “evoke individual prejudice, biases or stereotypes” [48]. On the other hand, deep-level diversity refers to those features relevant to psychological aspects of the group members that are not apparent [49]. Broader and more intangible than the earlier type, deep-level diversity may indicate values [50], personal traits [51], as well as attitude, preferences and beliefs [46]. Due to their latent nature, these diversity features can be expressed through behaviors, verbal and nonverbal communication, and personal information [49]. Figure 2.1 shows a visual representation of surface and deep-level diversity.
Prior diversity studies exist within fields such as psychology [46], [52], organisation management [53]–[55], and team decision making [56]. In this thesis, given the availability of the data, we will focus on the following diversity features: the demographic information of the crowd, such as age, gender, nation of origin makes up surface diversity. For deep-level diversity, we will consider knowledge diversity, education diversity, and motivation diversity. In the following discussion, we explain why knowledge, education, and motivation diversity are selected as the major deep-level diversity features.

Given the previous dichotomy of surface and deep-level diversity, knowledge diversity falls under the latter category. Deep level diversity also include skills, abilities (cognitive, physical) and experience [32].

Scholars have long suspected a relationship between knowledge diversity and innovation capability within a social unit [57], [58]. They theorize that the more diverse the knowledge of a social unit, the more likely it is to enhance the firm’s absorptive capacity and therefore lead to innovation [59]–[66]. Scholars define the measure of knowledge diversity as the number of domains any individual has prior experience in. Some also call it "work history experience" [67]–[69].

Education diversity is another deep-level feature explored in this thesis. Many scholars have suggested that education diversity has influence on both the internal cooperation and external openness of an organization [70]–[73]. Heterogeneity in education levels not only overcomes “typical functional bias” in social units such as firms, but such functional diversity might further contributes
to external knowledge sourcing and external communication [70], [73]. In the context of open innovation, educational diversity measured by the different level of academic degrees is also key to studying the complex cognitive task that are offered by the crowd [72], [74].

Another important deep-level diversity feature that we study is motivational diversity. As previous scholars point out, the motivational profile of solvers’, those who participate in an open innovation challenge, has significant effects on their involvement and performance in open innovation [29]. Section 2.2.3 furthers this topic by introducing literatures that study crowd motivations in open innovation. I discuss the mixed method approach to extract motivation from the ACS solvers in section 3.2.2.

2.1.3 Population vs. Individual Diversity

Population diversity is a key dimension for this study. It is commonly used and discussed in diversity literature across disciplines. There is a widely accepted definition of population diversity by scholars. Lieberson (1969: 851) defines population diversity as: a position of a population along a homogeneity-heterogeneity continuum that are classified by one or more variables [75], [76]. Similar definitions have been proposed by Gibbs and Martin (1962) and used by Labovitz and Gibbs (1964), Gibbs and Browning (1966), Rushing (1968, 1976), and Sammuel and Mannheim [76]–[79].

However, there are numerous ideas on how to operationalize the concept and measure population diversity. Stanley Lieberson suggests there are at least four dimensions for calculating diversity in the context of population: (1) diversity within a population, (2) diversity across populations, (3) polytomous and (4) dichotomous variables for a population [80]. Rooted in the field of ecology, Pielou argues that "a diversity index may be chosen to reflect both the absolute number of groups present, 'species abundance', and the relative frequency with which they are present, ‘evenness’" [81].

An index of such is called the "coefficient of unalikeability" [82]. To analyze categorical data, such as the ones collected for this thesis, the traditional measures of variability such as variance and standard deviation do not offer a compelling case to understand the population distributions. This is because the concept of "variability" for categorical data often differs from that for quantitative data. In the case of quantitative data, the concept of variability, operationalized through variance and standard deviation, asks "how much the values differ from the mean"[82]? In the case of categorical data, for example, the data on a population’s country representation, such question on "how far" is any
data point from the mean does not make sense. Instead, "how often the observations differ from one another?" [82] is more suited. In other words, how often do the samples in the population come from different countries from one another? This approach defines the concept of variability in categorical data as "unalikeability." The more "unalike" the values in a category are, for a given population, the more diverse/heterogenous the population is in that category.

The coefficient of unalikeability describes the probability of two observations selected randomly from a population that will have a different categorical attribute. It follows the formula of:

\[ u = 1 - \sum (p_i)^2 \]  [82]

where \( p_i \) is the share of proportion in a categorical attribute of that population.

The value of \( u \) ranges from 0 to 1. If the population is perfectly homogeneous in that categorical attribute, then \( u = 1 - (1)^2 = 0 \). Inversely, \( u \) equals one means a perfectly heterogeneous, or diverse categorical attribute in that population. If the population comprises equal proportion of males and females (50% each), then \( u = 1 - (0.5)^2 - (0.5)^2 = 0.5 \). As a comparison, if the population comprises 90% of males and 10% of females, then \( u = 0.18 \), a value smaller than the prior case of 0.5 and therefore, a less diverse gender distribution [83].

The coefficient of unalikeability has been widely adopted and developed by disciplines. In different disciplines, they operationalize the concept and measure variability under different names, such as "index of qualitative variation (IQV)" in sociology [84], or "index of linguistic homogeneity" in linguistics [85]. Their essence is the same: a measurement of variability based on the proportion of possible pairings that are unalike in a population.

Another frequently used measure for unevenness in population distribution is the entropy index of diversity, or information-based statistics, or the Shannon index [86], [87]. The entropy index follows the formula of:

\[ h_i = - \sum Q_r \ln \left( \frac{1}{Q_r} \right), (r = 1, 2, 3 ... n) \]  [86], [87]

where \( Q_r \) stands for proportion of the population of group \( r \). Like the coefficient of unlikability above, it also ranges from zero to one. When the value equals zero, it means there is only one single group, and when the value equals one, it means all groups are evenly distributed in the population.

Both the coefficient of unlikeability and entropy index of diversity are readily applied measures of population diversity. They are not just a measure for the homogeneity of certain categorical
attributes within a population, but also a measure for comparing the relative diversity of groups with a similar spectrum of characteristics [83].

On a separate topic, there is rather sparse literature on the concept of individual diversity. Wulf defines individual diversity as "the breadth of experience of a single individual" [88]. While a universal definition is absent to define individual diversity, we observe shared theme of the uniqueness of individual in comparison to the definition of population diversity. To capture this theme of uniqueness, we propose a centralizing method to measure individual diversity, essentially by asking: who is the modal individual in a particular population? Differing from the traditional statistical methods on central tendency such as deriving means, median and mode for each attribute, this method permutes multiple attributes until it identifies the most representative individual with most common attributes with other people. Figure 2.2 is a visual representation of population and individual diversity.

![Figure 2.2 A Visual Comparison of Individual vs. Population Diversity](image)

2.1.4 Absolute vs. Relative Diversity

Traditional measures represent diversity by only counting the absolute magnitude of a single attribute and comparing its proportion within the group. The drawbacks of that approach include: 1) the measures may not be monotonically related to diversity, 2) the measures do not account for the interplays of attributes within a group, and 3) the measures become less compelling where there is more than one variable for a given attributes of interest [89]. To overcome these limitations on measuring diversity, Meyer McIntosh (1992) proposed a method of incorporating the traditional
measure with multidimensional modals in order to describe how “differences along one-dimension correlate with differences along another dimension” [89], [90]. Over time, the measures of absolute and relative diversity evolved in disciplines such as sociology, biology, urban planning and many others.

Stemming from the traditional proportion of a single-attribute diversity measures, interaction probability-based indices have become a norm for measuring both absolute and relative diversity [75], [91]. This concept measures the likelihood of two randomly selected individuals from a population to be different on a given category [83], [89]. Several interaction-based indices have been proposed across fields, e.g. the Shannon–Wiener Index [92], Simpson index [93], and fractionalization. From here, some scholars introduce the deduced measures of "Relative Diversity Measure (ReID)" from assessing the "diversity distance" between the different absolute diversity indices of groups [75].

While some scholars propose measures to assess relative diversity across groups, others argue that the concept of relative diversity is "non-existent" [94]. In absence of an external criterion, any attempt in describing the similarity or relative comparison is "without relevance" [94]. In the case of medicinal chemistry, Hans-Jörg Roth argues that without an "assay", an external frame of reference such as the functionality of certain molecule, a simple comparison on the "structural diversity" does not necessarily distinguish the diversity of "biological effects" between two substances. In other words, similarities cannot be measured in an absolute sense, nor can relative diversity be measured without external criteria [94].

Depending on the disciplines and purposes of measuring diversity, the debate on what is absolute and relative diversity and how to operationalize the two concepts is still ongoing.

2.2 Why Pursue Open Innovation?

A prize competition as an open innovation mechanism, connects the solution seekers (organizations) and solvers (the crowd) from both ends via the broadcast problem. In this section, I look into the policy statements and literature to explain why organizations and individuals engage with open innovation.
2.2.1 Why do Organizations Use Open Innovation in the Public Sector?

The first recorded open innovation prize challenge dated back to the 17th century in Europe, where six sea-faring countries each offered a prize to stimulate innovative solutions on finding the longitude at sea, aptly named the “Longitude Challenge” [95]. Over time, the concept and practice of open innovation evolved in both the public and private sector. Many scholars have captured and theorized this process, including Chesbrough [96], [97], Eric von Hippel. [98][99] and so on.

In this thesis, open innovation refers to a distributed innovation process where anyone in the world may contribute through voluntary self-selection and decentralized knowledge flow [99]. The public open innovation processes studied in this thesis follow this definition, where the various forms of open innovation mechanisms facilitate citizens and other governmental stakeholders to contribute innovative knowledge in the public domain. The five main open innovation initiatives used by U.S. federal agencies are: (1) crowd-sourcing and citizen science, (2) idea generation, (3) open data collaboration, (4) open dialogue, and (5) prize competition or challenge [100]. In this thesis, we focus primarily on the last category: prize competition and challenges, where federal agencies act as seeker, using cash prizes and other incentives to reach problem-solvers from the crowd to address an issue in a defined timeframe [101]. This particular setup enables federal agencies to pay for the best result, save time and resources, engage innovators with diverse skill sets, and create opportunity for public-private partnerships [102]. In the past decade, countries other than the U.S., such as Australia and Singapore, have adopted public prize challenges and manifested it through national policies and programs [103]–[106]

In the U.S., the goals for the public sector to use open innovation are oftentimes agency dependent. However, there are several common traits. The United States Government Accountability Office identified five non-exclusive high-level objectives behind public agencies’ open innovation strategies: (1) collect information and perspectives; (2) develop and test new ideas, solutions, or product; (3) enhance agency capacity; build or expand community; (4) and increase public awareness [100]. The detailed descriptions of each purpose are summarized in Table 2.2.
Table 2.2 Purposes That Agencies Can Use Open Innovation to Achieve [100]

<table>
<thead>
<tr>
<th>Purpose</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Collect information and perspectives</td>
<td>Agencies can collect the perspectives of a broad group of citizen and external stakeholders to inform decisions about policies, plans, and the allocation of resources.</td>
</tr>
<tr>
<td>Develop and test new ideas, solutions, or products</td>
<td>Agencies can efficiently engage a broad range of citizens and external stakeholders in developing new ideas, solutions, or new products ranging from software applications to physical devices [...] can also have them evaluate the quality and feasibility of the ideas [...] also to stimulate the creation of new markets and companies that will then commercialize products and technologies.</td>
</tr>
<tr>
<td>Enhance agency capacity</td>
<td>Agencies can leverage the time, resources and expertise of citizens and external stakeholders to supplement their internal resources, data, and expertise.</td>
</tr>
<tr>
<td>Build or expand community</td>
<td>Agency can establish or enhance collaboration among citizens and external stakeholders or organizations interested in an issue.</td>
</tr>
<tr>
<td>Increase public awareness</td>
<td>Agency can provide participant or the broader public with balanced and objective information and data to help them understand an issue.</td>
</tr>
</tbody>
</table>

Another set of policy objectives is also suggested by the Office of Science and Technology Policy (OSTP) in their biennial report on the implementation of federal prize authority: (1) improving government service delivery; (2) finding and highlighting innovative ideas; (3) solving a specific problem; (4) advancing scientific research; (5) developing and demonstrating technology; (6) informing and educating the public; (7) engaging new people and communities; (8) building capacity, and (9) stimulating markets [11]. Compared to the purposes identified by the Government Accountability Office, there are large overlaps in the OSTP proposes, as indicated by Table 2.3.

Table 2.3 Comparison of Goals of Public Open Innovation Challenge by GAO and OSTP

<table>
<thead>
<tr>
<th>Goals identified by GAO [100]</th>
<th>Goals identified by OSTP[11]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Collect information and perspectives</td>
<td>Finding and highlighting innovative ideas</td>
</tr>
<tr>
<td>Develop and test new ideas, solutions, or products</td>
<td>Solving a specific problem; advancing scientific research; developing and demonstrating technology</td>
</tr>
<tr>
<td>Enhance agency capacity</td>
<td>Improving government service delivery</td>
</tr>
<tr>
<td>Build or expand community</td>
<td>Engaging new people and communities; building capacity, and stimulating markets</td>
</tr>
<tr>
<td>Increase public awareness</td>
<td>Informing and educating the public</td>
</tr>
</tbody>
</table>
Evaluating the usage of open innovation from an operational perspective, it also offers an alternative to the traditional grants and contracts mechanism for some public agencies in idea or solution solicitation. According to Felin & Zenger (2014), open innovation assists government organizations to move from a closed innovation paradigm that relies on pre-selected vendors and contractors, to an open paradigm that encourages citizens to participate and collaborate with the government [107]. Compared with federal grants and contracts, open innovation has the following benefits: (1) the ability to attract a broader spectrum of participants and ideas by reducing costs and bureaucratic barriers to participation; (2) the potential of leveraging a sponsor’s financial resources; (3) the ability of federal agencies to shift the technical and other risks to contestants; and (4) the capacity to educate, inspire, and potentially mobilize the public around scientific, technical, and societal objectives [108]. In a nutshell, it helps reduce cost and lower risk for the operating agencies, broaden their audience reach and potential educational impacts. To elaborate on the benefits of reduced cost of open innovation, it allows solution seekers (ie. public agencies) to only pay for the successful results that meet the criteria, rather than paying for failed or nominal solutions as it would in the traditional grants and contracts mechanism [108].

2.2.2 Diversity as a Goal of Open Innovation by Public Agencies and Why

As discussed earlier, public agencies pursue open innovation for many reasons, and reaching diversity of solvers is one of such motivations. It is common to find a diversity objective, in one way or another, across challenge mission statements, reports, work documents, and relevant policies [11], [100], [102], [105], [109].

Back in 2007, The National Science Foundation was tasked to experiment running open innovation challenges with funds appropriated from the House Appropriations Subcommittee on Science, State, Justice, and Commerce [22]. Before launching any challenge, NSF convened a group of experts in studying the potential benefits and setting up success metrics for the upcoming challenges. In their report, NSF identifies a series of near-term impacts of prize challenges, including “attracting diverse participants in the competition and involving students and young professionals.” In further details, it defines “diverse participants” as those contestants who are “somewhat different from the scholars and academic institutions that typically apply for NSF grants” [22].
In the Crowdsourcing and Citizen Science Act [110], the Congress highlight the societal benefits of a diverse population in open innovation prize challenges with the following: “federal projects that use crowdsourcing and citizen science do not solely benefit the U.S. Government; they also have positive impacts on the citizens who participate in them.” In particular, they define reaching a diverse population as “moving beyond working only with established entities (e.g., universities, private firms, non-governmental organizations) through contracts and grants” [110]. This indicates the expectation of open innovation in enabling government to engage with a broader public than it would not otherwise.

Furthermore, the Federal Community of Practice for Crowdsourcing and Citizen Science (FedCCS) is a 400-people organization made up of employees from over 60 federal agencies. They meet regularly to discuss plans to advance crowdsourcing and citizen science. As stated in their official website, a central question to their work is also associated with the diversity of solvers: “how can federal agencies engage the public directly and creatively, as partners to enhance agencies’ diverse missions” [111]?

A report measuring the progress of open innovation by the OSTP suggests that, for the fifth consecutive year, the most common goal reported by agencies in running prize challenge is to “engage new people and communities.” This goal outruns other objectives such as “solving a specific problem,” “developing technology,” and “finding and highlighting innovative ideas” [11]. While the exact wording differs, but “new people and community” essentially carries the same massage as diversity in this report.

Apart from the policy examples above on achieving diversity of solvers in open innovation, below is a table recording similar intents by a selected group of STEM federal agencies who actively exploit prize challenges.

<table>
<thead>
<tr>
<th>Selected STEM Federal Agencies</th>
<th>Policy Intentions Regarding Open Innovation</th>
</tr>
</thead>
<tbody>
<tr>
<td>National Aeronautics and Space Administration (NASA)</td>
<td>[…] By issuing these challenges, the agency (NASA) readily increases its creative capacity and reach by tapping into diverse talent from around the world [23]</td>
</tr>
<tr>
<td></td>
<td>[…]Many federal agencies and organizations (including NASA) around the world have begun harnessing the perspectives, expertise, and enthusiasm of “the crowd” outside their walls to reduce costs, accelerate projects, enhance creativity, and better engage their stakeholders [112].</td>
</tr>
</tbody>
</table>

NASA increasingly collaborates with a more diverse set of entities in the broader national and international citizenry through a suite of open innovation initiatives.
Table 2.4 (Continued): Selected STEM Federal Agencies and Their Policy Intents on Diversity Via Open Innovation

<table>
<thead>
<tr>
<th>Selected STEM Federal Agencies</th>
<th>Policy Intentions Regarding Open Innovation</th>
</tr>
</thead>
<tbody>
<tr>
<td>National Aeronautics and Space Administration (NASA)</td>
<td>(Cont’d) By sharing the outcomes of these initiatives, we (NASA) hope to inspire further efforts to feature the world’s people in our work of innovation and discovery— and to show individuals and groups from around the world the value of their participation with NASA, encouraging them to join us in the pursuit of knowledge, innovation, and exploration[113]. Equally notably, the agency has with increasing frequency been looking for participation beyond commercial firms and the academic sphere and is also inviting the broader national, and in many cases international, citizenry to help solve technological problems and contribute to the advancement of space-related science [113].</td>
</tr>
<tr>
<td>National Science Foundation (NSF)</td>
<td>Among the relevant indicators of positive near-term impact of Innovation Inducement Prizes at the National Science Foundation could be: whether the contests attract large numbers of contestants; whether those contestants are a more diverse group than the traditional NSF constituency[…][22]. “Near-term impact” refers to the subsidiary purposes of prize contests, correlates of successful administration that can be measured and evaluated, such as attracting diverse participants in the competition, involving students and young professionals, inducing private parties to support contestants, stimulating public interest in science and technology, and enhancing the public reputation of the prize-giving institution [22]. Because one of the purposes of an NSF innovation prize program is to strengthen U.S. innovative capacity, it is appropriate to restrict participation to U.S.-incorporated or chartered entities and teams led by U.S. citizens or permanent residents. [22].</td>
</tr>
<tr>
<td>Department of Energy (DOE)</td>
<td>Prizes may be appropriate for use when: 1) Highlight excellence in a particular area to motivate, inspire, or guide others; 2) Increase the number and diversity of individuals, organizations, and teams that are addressing a challenge of national or international significance; […] 8) Expand a program's reach to citizen solvers and entrepreneurs of diverse backgrounds, skill sets, and experience; 9) Bring out-of-discipline perspectives to bear[24].</td>
</tr>
<tr>
<td>U.S. Department of Health and Human Services (HHS)</td>
<td>The IDEA Lab’s Open Innovation service provides the Department with expert knowledge of alternative tools available to bring opportunities to problem solvers everywhere. Specifically, we provide value by: […] posing problems and opportunities to all available pools of talent, increasing the number of people, organizations and companies working on a problem and stimulating markets to develop a robust eco-system of approaches […] engaging communities to create networks of current and future problem solvers [114].</td>
</tr>
<tr>
<td>National Institute of Standards and Technology (NIST)</td>
<td>Open Innovation focuses on outcomes and results, not on specific requirements. The problem solvers (aka Challenge participants) determine the “how” and the “solution” by using their creativity to reach the desired goal […] The mission of NIST Public Safety Communications Research Division (to use) Open Innovation is to create a framework in which we can work with individuals, companies, organizations, and academic institutes in a rapid, more collaborative ways than traditional engagements [115]. (NIST and) the challenge partners understood that the experts who could produce better materials could be found in a hugely diverse set of communities, from aerospace to automotive to sports medicine […] (We are) to implement prize challenges in order to reach solvers from around the world to help us reach our goals […] (we) encourage collaboration and partnerships amongst industry, small businesses and government contractors to accomplish our goals [115].</td>
</tr>
<tr>
<td>Office of Science and Technology Policy (OSTP)</td>
<td>For the fifth consecutive year, the most common prize competition goal reported was engage new people and communities, reported by 71.4% and 73.2% of active prize competitions in FY17 and FY18, respectively [11].</td>
</tr>
</tbody>
</table>
Now that we have seen how different governmental bodies claim to pursue diversity in open innovation, it is time to understand why they have such pursuit.

Literature and policy statements suggest there are two prominent benefits of reaching diversity of solvers in open innovation: its societal value and functional value.

The societal benefit for public agencies to reach a diverse population through open innovation is oftentimes aligning with their agency missions and core objectives. An example would be NASA, whose core values encompass “safety, integrity, teamwork, excellence, and inclusion” [116]. Therefore, reaching more diversity of solvers through open innovation directly contribute to one of NASA’s missions.

In addition, many federal agencies face a demographic “cliff,” particularly in age, within their workforce. As of June 2019, only 6.3% of full-time federal employees are under 30 years old. Roughly one-third of the federal employees onboarded at the beginning of FY2019 will be eligible for retirement by the end of FY2023 [117]. Such an aging workforce will lead to gaps in knowledge and skillsets among the employees, between what senior members know and what is available in the systems for new comers [118]. Therefore, by broadcasting the problems to the external crowd and potentially reaching a diverse population, open innovation challenges may help to compensate the negative impacts of an aging federal workforce, by providing an channel for different groups to solve and collaborate on the problems [119][120].

In terms of functional benefits, reaching a diverse group through open innovation is believed to increase the chance of finding a good solution to the broadcast problem. While the mechanism behind such assumption is still being explored, there are a few schools of thought explaining this phenomenon from different angles. Szajnfarber et al. summarize them in four categories: (1) random draws, (2) talent search, (3) perspective identification, and (4) “gig” matching [28]. The “random draws” perspectives view the broadcast process as a stochastic tournament [121], wherein each search represents an independent draw from a pool of solutions that have normally distributed quality [122], [123]. The “talent search” perspective focuses on sampling from the solvers’ capability, or their level of expertise [122]. Prize competition provides a platform for the most talented solver for a specific problem to reveal themselves [28]. “Perspective identification”, on the other hand, describes how prize competition allow the identification of “novel solving heuristic-solution pairs” [62], [124]. Under the assumption that experts tend to be cognitively entrenched [125] and relying on their typical solving heuristic, broadcast search like prize challenges allows the seeker to approach and interact with solvers
of different heuristics for the same problem. These heuristics are local to the solvers [59] but might be distant, novel, and occasionally better to the seekers [28]. Finally, “gig” matching implies that broadcast search enables seekers to reach “core domain experts” [62], who are not employed by the organization yet capable of to solve the problem. Under certain circumstances, they could be considered for employment by the seeker organization [28].

To summarize, there is a consistent policy emphasis on reaching a diverse population via public open innovation challenges. There are societal and functional benefits in broadcasting a problem outside the agencies’ boundaries. However, whether prize challenges indeed reach a more diverse solver base or not has not been studied, partly due to the lack of suited data, making it a key research question for this thesis.

2.2.3 Why does the Crowd Participate in Open Innovation?

Scholars have long associated individual’s performance with their ability and motivation [126]–[128]. Maier et.al theorize a functional relationship between the three aspects:

\[ \text{Performance} = f(\text{motivation} \times \text{ability}) \] [127], [128]

In this simple multiplicative relationship, performance is concurrently dependent on both motivation and ability. The absence of any one of these factors will lead to zero performance. According to Amabile (1998), motivation by itself will unlikely lead to high performance unless accompanied by a minimum level of skills and knowledge. However, a lack of motivation does not affect skills being stable or applied to other areas [129]. Conversely, others suggest that while motivation might have substantial influence on solvers’ perspective, it is actually weakly associated with their performance [130].

With the emergence of open innovation in different sectors, motivations have been investigated extensively. Hars and Ou, Hertel et al., Lakhani and Wolf studied the self-rated importance of motivations for solvers in user communities and open projects [131]–[133]. Acar et al. examine the correlation between motivations and solution appropriateness in open innovation challenges [30]. Frey et al. study motivations in order to offer insights for firms on whom they should attract for their open innovation projects. While the precise mechanism between motivation and
performance remains ambiguous, there is a consensus in the literature regarding the role of motivation as a key factor to understand the crowd and their contribution [29].

Many of the above scholars base their analysis on the well-established psychological framework on human motivations, by distinguishing between intrinsic and extrinsic motivations [129], [134]. Motivations are intrinsic when engaging and finishing a task is valued by the task itself [29], [135]. In open innovation context, intrinsic motivations are oftentimes associated with sheer fun and the enjoyment of developing innovative solutions to challenging problems [136], [137]. Fulfilling intellectual satisfaction is another way of describing such motivations [137]. On the other hand, extrinsic motivations value tasks with goals that are not related to conducting the task itself [135]. Scholars identify a few recurring external motives such as: career concerns, payment and personal need for innovations [29]. Given the similarity between the above-mentioned motivations of “personal need for innovation” and “enjoyment of developing innovative solutions to challenging problems”, scholars provide further distinct the two. The former motivation is defined as: “by participating actively, individuals hope to obtain a solution that better fits their needs (in work or in personal life).” Therefore, it is an extrinsic motivation. The later motivation is intrinsic because it focuses more on the enjoyment [29], [136].

If layout all motivations on an imaginary spectrum, then intrinsic and extrinsic motivations sit on the opposite poles. There are also other factors and nuances to human psychological motivations. For example, Lakhani and Wolf introduced a threefold categorization of user motivations, that is composed of: (1) enjoyment-based intrinsic, (2) obligation/community based intrinsic, and (3) extrinsic motivations [138]. Acar introduces a classification based on the self-determination theory in which he views motivation as a spectrum, with intrinsic and extrinsic motivations at the two ends, and a number of internalized motivations in-between [30]. Particularly, he adopts the following five categories: intrinsic motivation, learning motivation, pro-social motivation, social motivation, and extrinsic motivation. In "And the winner is . . . Capturing the promise of philanthropic prizes", a McKinsey Company report on prized challenges, Ken Davidian, formerly of the NASA Centennial Challenges, was quoted to describe the motivations of prized challenge participants as “4Gs”: goal, glory, guts, and gold [139]. To elaborate, “goal” refers to a type of intrinsic interest towards the challenge; “glory” defines the recognition and prestige associated with winning a challenge; “guts,” the challenging process of solving a problem or a challenge; and “gold,” the monetary or other material incentives. In addition, Davidian also argued that, “gold” tends to rank least in popularity among the 4Gs, which is surprising given that the name of “prize” challenges and their usual incentives setup based on prize
money. Table 2.5 is a comparison of how motivation categories are considered by the aforementioned literature.

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>Guts</td>
<td>Enjoyment-based intrinsic motivation</td>
<td>Intrinsic motivation</td>
</tr>
<tr>
<td>Goal</td>
<td>Obligation/community based intrinsic motivation</td>
<td>Prosocial motivation</td>
</tr>
<tr>
<td>Gold</td>
<td>Extrinsic motivations</td>
<td>Extrinsic motivation</td>
</tr>
<tr>
<td>Glory</td>
<td></td>
<td>Learning motivation</td>
</tr>
</tbody>
</table>

2.2.4 What are the Differences Across Types of Participants?

In addition to measuring the diversity of solvers in terms of their demographics, knowledge, education and motivation, we also wish to analyze how these diversity features may affect their performance in open innovation challenges.

Jeppesen and Lakhani argue that technical and societal marginality contribute to problem-solving capability for solvers in open innovation [62]. In this context, technical marginality refers to the distance of an individual’s technical expertise to the field of problem. They argue that in open innovation challenges, the odds of submitting a winning solution is positively related to the technical marginality of the solver. Societal marginality measures how far away an individual is from the “establishment” or norms of the professional community. They reveal that being a female in a science community, with an increased societal marginality, contributes to more successful solutions than their counterparts with less distance to the societal norms in that community. Their conclusion favoring female performance is in contrast with the study by Balafoutas and Sutter (2019,) who argue the performance by males is higher in a tournament under uncertainty and ambiguity. They also find that women are less likely to choose to compete, when uncertainty and ambiguity are raised [141]. This is consistent with the findings of Muriel Niederle, Lise Vesterlund (2007,) where women are twice less likely to enter a competitive tournament than men [142].
Others have looked at how divergence in expertise levels, or knowledge diversity might influence solvers’ commitment of participation. Körpeoglu and Soo-Haeng Cho suggest that high-expertise solvers raise their efforts when there are increased competitions. In other words, heterogeneous expertise levels respond to different incentive levels [143].

These researches show how differences in diversity features, such as technical expertise and gender, will lead to divergence in solvers’ performances in open innovation challenges, reflected in their self-selection of entry, commitment, or solution quality.

2.3 Research Gaps

There are a few research gaps emerging from the previous sections. First of all, there is a need to consider diversity from its multidimensional nature. Based on a synthesis of literature review across many fields, such discussion is now presented in section 2.1. It considers the nuances of diversity and proposes perspectives from surface vs. deep level, absolute vs. relative and population vs. individual diversity.

As we have seen in the previous section, public agencies, particularly U.S. public agencies have been actively investing and engaging in open innovation challenges, in a hope to increase diverse participation in STEM fields. However, due to a lack of empirical data, there has been a gap regarding whether open innovation challenges are indeed achieving the diversity goals. And if so, to what extent. In the later sections, this thesis tests these questions with the ACS data.

Another research gap exists in the studies of solvers’ motivations in open innovation. Particularly, what is the role of motivation in terms of yielding good solutions in open innovation challenges? We address this inquiry by deriving the motivation from the ACS crowd, by applying a mixed method of inductive coding and natural language processing.

Lastly, there is a gap regarding whether “more diverse” solvers are more likely to deliver quality solutions, which we test with the ACS data and present the results in section 4.
Chapter 3 Research Design and Methodologies

3.1 Context and Data

This thesis leverages a case study and applies a mixed method to study the research problems raised earlier. In order to address the research gaps identified, we need empirical data on the solvers (the crowd) and their solutions from a public prize challenge, ideally on a STEM-related problem. To understand the extent of achieved diversity performance among the solvers, we need a comparative dataset on the diversity performance of a reference population. To make the connection between solution quality and diversity attributes from the crowd, we first need a benchmark for identifying the “better” solutions from the “worse.” The Astrobee Challenge Series (ACS) is a field experiment that provides exactly such information. It is a prize challenge launched by a STEM federal agency, NASA, seeking solutions on innovative robotic arm designs from a global crowd.

3.1.1 Astrobee Challenge Series (ACS)

In May 2018, NASA launched an open innovation series of 17 challenges focusing on the development of a robotic arm for Astrobee. Astrobee is a free-flying robotics system to be used inside the International Space Station, acting autonomously or via remote-control to assist astronauts in their daily operations [144]. While NASA has already deployed Astrobee the robot on the International Space Station, the ACS seeks innovative solutions for upgrading the system performance by adding an attachment and orientation arm to it [28].

ACS was launched on Freelancer.com, one of the largest open innovation websites with an active solver base of more than 41 million users [145]. Freelancer.com was chosen as the online partner for its multidisciplinary solver base compared to other third-party open innovation platforms. It enables a wide range of challenge problems, including mechanical, electrical, and software architecture problems to be conducted in one ecosystem [28]. The challenge series was administered from May 2018 to June 2019, with each challenge probing an area of an interdisciplinary robotics system at various levels of complexity and awards.
The ACS was designed as a field experiment, where SzajnLab, a research team at George Washington University, worked with NASA on designing the requirements of the 17 respective challenges for the robotic arm. An internal group of NASA roboticists was also tasked to design a robotic arm for the Astrobee. Their internal solution serves as a surrogate in terms of determining the solution quality. Table 3.1 summarizes the challenge problems along with reward values, figure of merits, number of submissions received and quality comparison to the internal NASA designs. Additionally, SzajnLab designed and implemented a pre-registration and a post-completion survey for the participating crowd, of which this research benefits greatly. These surveys were introduced as part of the competing rules for the crowd, collecting information with consents on their demographics and other experience.

ACS is particularly suited for the discussion of this thesis for the following reasons. First, it presents a real-world problem in a STEM field, while being sponsored and managed by a federal agency. Second, its field experiment setup and rich data enable analysis on both the solvers and the solutions generated via the prize challenge. During its prize phase of over 1.5 years, the ACS launched 17 challenges and was able to track solver participation and solution outcomes. The collected demographics information makes the ideal crowd diversity data. The fact that a group of NASA roboticists generated solutions allow us to compare the external crowd with the internal solvers tasked the same problems.

Table 3.1 Summary of challenge problems and submitted solutions [28]

<table>
<thead>
<tr>
<th>ID</th>
<th>Challenge descriptiona</th>
<th>Prize</th>
<th>FOMb</th>
<th>Responsec</th>
<th>Qualityd</th>
</tr>
</thead>
<tbody>
<tr>
<td>SRA</td>
<td>Autonomous deployment, attachment and positioning systems.</td>
<td>$5000 Kg</td>
<td>18</td>
<td>N/A</td>
<td></td>
</tr>
<tr>
<td>SFA</td>
<td>Autonomous deployment and positioning system</td>
<td>$4000 Kg</td>
<td>8</td>
<td>N/A</td>
<td></td>
</tr>
<tr>
<td>SAM</td>
<td>Autonomous attachment system</td>
<td>$1500 Kg</td>
<td>14</td>
<td>Better</td>
<td></td>
</tr>
<tr>
<td>SCA</td>
<td>Autonomous deployment mechanism</td>
<td>$1500 Kg</td>
<td>9</td>
<td>Better</td>
<td></td>
</tr>
<tr>
<td>SPAM</td>
<td>Autonomous positioning and attachment system</td>
<td>$4000 Kg</td>
<td>15</td>
<td>Better</td>
<td></td>
</tr>
<tr>
<td>EMA</td>
<td>Mechanical elements of SRA</td>
<td>$4000 Kg</td>
<td>17</td>
<td>N/A</td>
<td></td>
</tr>
<tr>
<td>CDPD</td>
<td>Electronic elements of SRA</td>
<td>$1500 W</td>
<td>5</td>
<td>N/A</td>
<td></td>
</tr>
<tr>
<td>RASA</td>
<td>Software architecture for SRA</td>
<td>$1500 LOC</td>
<td>6</td>
<td>Better</td>
<td></td>
</tr>
<tr>
<td>PSA</td>
<td>Positioning function of RASA</td>
<td>$500 LOC</td>
<td>7</td>
<td>N/A</td>
<td></td>
</tr>
<tr>
<td>AM</td>
<td>Mechanical elements of SAM</td>
<td>$500 Kg</td>
<td>19</td>
<td>Better</td>
<td></td>
</tr>
<tr>
<td>MDC</td>
<td>Mechanically driven clamp</td>
<td>$250 Kg</td>
<td>18</td>
<td>Better</td>
<td></td>
</tr>
<tr>
<td>ID</td>
<td>Challenge description</td>
<td>Prize</td>
<td>FOM</td>
<td>Response</td>
<td>Quality</td>
</tr>
<tr>
<td>----</td>
<td>-----------------------</td>
<td>-------</td>
<td>-----</td>
<td>----------</td>
<td>---------</td>
</tr>
<tr>
<td>EDC</td>
<td>Electrically driven clamp</td>
<td>$250</td>
<td>Kg</td>
<td>11</td>
<td>Better</td>
</tr>
<tr>
<td>SDM</td>
<td>Single joint</td>
<td>$250</td>
<td>Kg</td>
<td>18</td>
<td>Worse</td>
</tr>
<tr>
<td>MIS</td>
<td>Attachment surface</td>
<td>$500</td>
<td>N</td>
<td>15</td>
<td>N/A</td>
</tr>
<tr>
<td>HMSA</td>
<td>Health monitoring software architecture</td>
<td>$250</td>
<td>LOC</td>
<td>7</td>
<td>N/A</td>
</tr>
<tr>
<td>EBD</td>
<td>Electronics box design</td>
<td>$250</td>
<td>Kg</td>
<td>20</td>
<td>Better</td>
</tr>
</tbody>
</table>

a For detailed description of each challenge, see [https://www.freelancer.com/nasa/astrobee](https://www.freelancer.com/nasa/astrobee)
b Figure of merit used to award winner (standard was: best FOM, given feasible). Lines of code (LOC)
c Number of solutions that were deemed to be at least conceptually complete (see Table 3.3 for solution quality scale)
d This column compares the winning solution to the internal reference problem. Note: since no decomposition was forced on the internal team, we are only able to compare to the internal solution where they chose to perform a sufficiently similar decomposition. The full problem is not directly comparable to the internal reference problem because we chose to slightly expand the workspace requirement to open the space of potential solutions. Doing so requires an additional degree of freedom, which necessarily adds mass.

**Data Source and Data Collection**

As mentioned, the pre-registration and post-completion surveys of the ACS constitute the crowd data in this study. The data collection process was operationalized as follows:

The landing page of the ACS on freelancer.com provided the context and the robotic arm design objective, along with minimal descriptions of each of the 17 sub-problem. The landing page served to attract a broad population with various degrees of interests in the context and competition of the challenge. Should any of them became interested in one or more sub-problem and wished to learn the specifics of the contest, he or she was asked to complete a registration survey. The survey included questions on basic demographic information, educational attainment depth, breadth of work experience, hobbies, and self-reported background in related projects. Upon finishing, a detailed prompt for each sub-problem and judging criteria would be shown, and this group became the “potential solver” in our data set. Upon seeing the full disclosure of the sub-problem prompts and requirements, each potential solver was free to spend as much or as little time to solve the specific problem they selected before the respective deadlines. Figure 3.1 [28] visualizes this process. Once they submitted their solutions, they became “solvers” in our data collection process. Each solver was again asked to fill a post-completion survey before they could end the process.
Measures - Demographic Variables

The registration survey collected data from the ACS crowd on demographic attributes such as age, gender, education, country of origin, experience level and so on. Age is defined by a 5-year interval, ranging from under 18 to 65 and older. Gender is defined as female or male. Education is defined as the highest educational degree attainment, including below high school, high school, Bachelor's degree, Master's degree and Doctorate’s degree. Country of origin is the reported country currently reside in. Experience level is defined as self-reported years of working experience in any of a technical field that was shortlisted in the survey. Table 3.2 shows the scale and types of variables for each demographic characteristic.

Table 3.2 Demographics collected from ACS crowd

<table>
<thead>
<tr>
<th>Independent Demographic Attributes</th>
<th>Variable Type</th>
<th>Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>Categorical</td>
<td>&lt;18;19-24;25-34;35-44;45-54;55-65;&gt;65</td>
</tr>
<tr>
<td>Gender</td>
<td>Categorical</td>
<td>Male, Female</td>
</tr>
<tr>
<td>Education</td>
<td>Categorical</td>
<td>Below High school, High school, Bachelors, Masters, PhD</td>
</tr>
<tr>
<td>Nationality</td>
<td>Categorical</td>
<td>Aggregated from more than 100 countries reported</td>
</tr>
</tbody>
</table>
Experience Level

<table>
<thead>
<tr>
<th>Discrete Integer</th>
<th>Self-reported continuous in integer years</th>
</tr>
</thead>
</table>

**Measures - Quality Solution Submitters**

In order to address RQ2, we need to understand the nuances among solvers based on the qualities of their solutions. Specially, we need to identify the subset of solvers whose solutions surpass those of the general crowd. We then compare the diversity performance, in terms of demographic and motivation data, between the two groups to understand if achieved diversity leads to improved innovation outcomes.

**Registrants** are the people who show general interests in the problems posted in ACS by filling up a registration survey on freelancer.com. There are 9215 registrants signing up for a total of 17 sub-challenges in ACS.

In this thesis, **Quality Solution Submitters** are the solvers whose solutions are completed in at least one aspect of the design, such as having a complete mechanical design, or a complete electrical design, or a software design. There are 85 individual solvers who handed in a total of 125 solutions in this group.

Upon receiving the solutions, the SzajnLab at the George Washington University conducted a preliminary quality check and categorized them based on the completeness level: incomplete, discarded, conceptually complete, mixed detailed and detailed, as shown in Table 3.3. As a reference, Quality Solution Submitters’ solutions fall under the category of “Mixed” and “Detailed.”

<table>
<thead>
<tr>
<th>Level</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Detailed</td>
<td>The design of the entire system has been specified (i.e., components have been selected or sized and their relationships defined).</td>
</tr>
<tr>
<td>Mixed</td>
<td>Detailed work has been completed in at least one aspect of the design, but other aspects remain at the conceptual level.</td>
</tr>
<tr>
<td>Conceptual</td>
<td>The conceptual design is complete; with additional design work it could become a detailed design.</td>
</tr>
<tr>
<td>Incomplete</td>
<td>Solution has design content, but it is not responsive to the problem as posed.</td>
</tr>
<tr>
<td>Did not submit/displaced</td>
<td>Downloaded the problem details, showing some interest, but did not submit any design content.</td>
</tr>
<tr>
<td></td>
<td>Removed before further coding.</td>
</tr>
</tbody>
</table>

Table 3.3 Solution Quality Scale [28]

1 In ACS, a solver was allowed to participate in more than one challenge, therefore was allowed to submit more than one solution. In the case where they submit multiple entries and only one pass the quality threshold defined by this thesis, they will still be considered as a quality solution submitter.
Sample Descriptions

Table 3.4 below presents the sample descriptions of both the ACS registers and quality solution submitters. While the majority of the attributes are self-explanatory, a few deserve further explanation. “Years of experience in technical fields” is the crowd’s reported years of working in fields from a pre-designed list, including electrical engineering, engineering drawing, industrial engineering and so on. Although the participants are free to select which and how many of Astrobotic challenges they wished to contribute, our findings indicate that the majority (54.5%) of registrants choose to participate in only one challenge. Despite quality solution submitters only accounting for 0.9% of the overall registered participants, they contribute over 49.02% of all submissions.

Table 3.4 Sample Descriptions of the ACS Populations

<table>
<thead>
<tr>
<th>Diversity Attributes</th>
<th>Sample of ACS Registrants (N = 9215)</th>
<th>Sample of ACS Quality Solution Submitters (N = 85)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>85.7% Male</td>
<td>90.4% Male</td>
</tr>
<tr>
<td></td>
<td>14.3% Female</td>
<td>9.6% Female</td>
</tr>
<tr>
<td>Age (median)</td>
<td>25-34</td>
<td>25-34</td>
</tr>
<tr>
<td>Highest Education Degree</td>
<td>46% Bachelor’s</td>
<td>52.9% Bachelor’s</td>
</tr>
<tr>
<td>Years of Experience</td>
<td>75.5% Less than 5 years</td>
<td>61.2% Less than 5 years</td>
</tr>
<tr>
<td>Total number of submissions</td>
<td>255</td>
<td>125</td>
</tr>
</tbody>
</table>

3.1.2 Reference Data for US Workforce

Data Source and Data Collection

To answer whether ACS has achieved diversity in the crowd, we need to establish a reference population. In order to answer how diverse the external ACS solvers are, we need to compare them to some internal solvers.

In this case, we choose the reference populations based on the problem domains and expected expertise required to solve the problems in ACS. NASA engineers are the ideal reference population because the ACS mirrors a NASA project and robotics falls under NASA’s key competencies as an organization. Therefore, NASA engineers who work on science and engineering sections across
different centers are the most appropriate reference population to represent the "internal solvers." We retrieve their demographics information from WICN, a public website managed by NASA Human Resources [146]. Although WICN proves to be a helpful data source, we were only able to access data on age and gender of the science and engineering (S&E) workforce at NASA. To be able to compensate for the absence of key surface diversity attributes such as countries of origin, we resorted to other public data sources such as Data USA. From there, we find data on the U.S. Robotics and Automation workforce, as well as the U.S. Aerospace workforce. While these datasets are not necessarily the same as the NASA workforce, they could be considered as appropriate surrogates. They represent U.S workforce who are similar to NASA, and are capable of solving the similar problems. Thus, we use a total of three datasets to reference the internal solvers, and compare them to the external crowd in ACS [147], [148]. Table 3.5 summarizes the three data sources.

Table 3.5 Internal Solver Data Sources

<table>
<thead>
<tr>
<th>Internal Solver Data Types</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>NASA Full-time Science and Engineer Workforce</td>
<td>Workforce Information Cubes for NASA (WICN) [146]</td>
</tr>
<tr>
<td>US Workforce in Robotics and Automation Industry</td>
<td>Data USA Robotics and Automation Engineering [147]</td>
</tr>
<tr>
<td>US Workforce in Aerospace Industry</td>
<td>Data USA Aerospace Engineer [148]</td>
</tr>
</tbody>
</table>

Sample Descriptions

The internal solvers in this thesis refer to the NASA Full-time S&E workforce, US workforce in robotics and automation industry and US workforce in aerospace combined. Below in Table 3.6 we present the sample descriptions of this group.

Table 3.6 Sample Descriptions of the Internal Solvers

<table>
<thead>
<tr>
<th>Diversity Attributes</th>
<th>Sample of Internal solver</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>76.9% male (NASA)</td>
</tr>
<tr>
<td></td>
<td>23.1% female (NASA)</td>
</tr>
<tr>
<td>Age (median)</td>
<td>45+ years old (NASA)</td>
</tr>
<tr>
<td>Highest Education Degree (median)</td>
<td>Bachelor’s degree (US Robotics)</td>
</tr>
<tr>
<td>Years of Experience (median)</td>
<td>15-19 years (NASA)</td>
</tr>
</tbody>
</table>
3.2 Methods of Analysis

3.2.1 How to Measure Diversity?

As presented earlier in Chapter 2, diversity is a complex social construct that can be defined from various dimensions. However, not all dimensions serve to directly measure diversity performance, nor is all dimensions suited for measuring every diversity attribute.

In this thesis, we present surface diversity and deep-level diversity as two categories for diversity attributes. Together, they provide an effective framework to categorize the various attributes collected in the case study of ACS. Surface diversity include attributes that are easy to observe, such as age, gender, and country of origin of the ACS crowd, while deep-level diversity include their education background, career experience (in fields and disciplines,) and motivation. This categorization help explains the relations of attributes clearly.

Relative diversity is the measurement on how group A compares to group B. In this thesis, it is operationalized as the comparison between the ACS crowd and the internal solver introduced above, who would typically solve the similar problems.

Absolute diversity, on the other hand, measures how group A compared to a context-dependent standard. In our case, it is operationalized by comparing the ACS crowd to multiple policy-derived diversity goals. See Figure 3.2 for a visual comparison of the two concepts in this thesis.

Figure 3.2 A Visual Comparison of Absolute vs. Relative Diversity
For example, due to its long absence, many federal agencies regard an increase of female’s presence as a departmental diversity goal. Many even set up relevant special emphasis programs to directly target this group [38], [44]. Therefore, in our thesis, reaching more females through open innovation challenge, is considered as an operationalization of reaching an "absolute diversity goal." The unit of variables in this case are the absolute numbers and proportions of females in the ACS crowd, compared to those in the internal populations.

Based on the earlier diversity and open innovation policy reviews, as well as conversations with field expertise and best educated estimation of diversity issue in the U.S. STEM fields, we formulate the following absolute diversity goals that will be tested by this thesis:

- Is the ACS crowd made up of more females (than the internal solver)?
- Is the ACS crowd made up of more young people (than the internal solver)?
- Is the ACS crowd representing more countries (than the internal solver)?
- Is the ACS crowd representing more career fields (than the internal solver)?
- Is the ACS crowd made up of less technically experienced people (than the internal solver)?
- Is the ACS crowd made up of less educated people (than the internal solver)?

Noted this is not an exhaustive list of "absolute diversity goals", but rather, a short-list given the context of this study. It serves as a possible set of standards for future policymakers to consider when there is a need for identifying and analyzing diversity goals from an “absolute” sense. Again, it showcases the complex nature of diversity as the definitions and specific measurement vary case by case. Later in Chapter 4 where results are presented per attribute, we will justify with relevant literature and policy for each of these absolute diversity goals in more details.

In terms of population diversity, this thesis adopts the coefficient of unalikeablity [82] discussed earlier, to study the heterogeneity within a population, a key concept in measuring diversity. The more unalike/heterogenous the values are within a category, the more diverse the population is in that category. However, not all attributes are suited to be measured by this coefficient. In this thesis, the ones that are appropriate to be measured from population diversity perspective are age, education background, years of experience, country of origin. For these attributes, it is not sufficient to simply measuring the absolute number and proportion as the earlier absolute diversity analysis do. There is a need to understand the heterogeneity or evenness of these attributes within the populations because such evenness often poses functional benefits or societal benefits to the organizations.
Take age as an example. Currently, many federal agencies suffer from a highly imbalanced age distribution that results in a demographic “cliff” [117], which causes knowledge and skill gaps within the organizations [118], hindering their innovation capacity. Therefore, an analysis on the heterogeneity of certain attributes among the ACS crowd is an important facet in the studies of diversity. Table 3.7 below summarizes how each attribute will be analyzed in this thesis.

Finally, individual diversity is analyzed by finding the most “typical” individual that best represents the ACS population. Given that our data is collected and organized as mixed data, sometimes as interval data, it is natural to assume combining the mode values of each attribute will lead us to the “centralized” individual. However, instead of amalgamating the mode values from each diversity attribute, the better approach is to permute all possible diversity feature combinations and order them by magnitude. Whichever combination of features contain the most population stands out to be the modal/typical ACS crowd [149], [150]. We apply this method in studying the modal ACS registrants and ACS quality solution submitters in answering RQ2.

Table 3.7 Overview of Method of Analysis

<table>
<thead>
<tr>
<th>Diversity Attribute</th>
<th>Diversity Category</th>
<th>Policy salient Diversity Dimensions</th>
<th>Relevant Policy Questions</th>
<th>Method of Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>Surface</td>
<td>Absolute; Relative</td>
<td>Is the ACS crowd made up of more females than the internal crowd?</td>
<td>Comparison on the absolute numbers (N) and proportions (k = y/x) of females between the ACS crowd and internal populations</td>
</tr>
</tbody>
</table>
| Age                 | Surface            | Absolute; Population; Relative     | 1. Is the ACS crowd younger than the internal crowd?  
2. Does the ACS crowd have a more heterogenous age distribution than the internal crowd? | 1. Comparison on median age and proportions (k = y/x) of young population ACS crowd and internal populations  
2. Compare the coefficient of unalikeablity (u) across populations |
| Country of Origin   | Surface            | Absolute; Population; Relative     | 1. Is the ACS crowd representing more countries?  
2. Does the ACS crowd have a more heterogenous country representation than the internal crowd? | 1. Comparison on absolute numbers (N) of countries between ACS crowd and internal populations  
2. Compare the coefficient of unalikeablity (u) across populations |
| Education Level     | Deep-level         | Absolute; Population; Relative     | 1. Is the ACS crowd less educated?  
2. Does the ACS crowd have a more heterogenous education level than the internal crowd? | 1. Comparison on proportion (k) of lower education level between ACS crowd and internal populations  
2. Compare the coefficient of unalikeablity (u) across populations |

2 We will justify how these dimensions are decided based on relevant context and policy in more details in Section 4.1 when presenting results on each attribute.
Table 3.7 (Continued) Overview of Method of Analysis

<table>
<thead>
<tr>
<th>Diversity Attribute</th>
<th>Diversity Category</th>
<th>Policy salient Diversity Dimensions</th>
<th>Relevant Policy Questions</th>
<th>Method of Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Years of Experience</td>
<td>Deep-level</td>
<td>Absolute; Population; Relative</td>
<td>1. Is the ACS crowd less experienced?</td>
<td>1. Comparison on proportion (k) of lower education level between ACS crowd and internal populations</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2. Does the ACS crowd have a more heterogeneous experience level than the internal crowd?</td>
<td>2. Compare the coefficient of unlikeliness (u) across populations</td>
</tr>
<tr>
<td>Work Experience</td>
<td>Deep-level</td>
<td>Absolute; Relative</td>
<td>Is the ACS crowd representing more career backgrounds?</td>
<td>Comparison on absolute numbers (N) of countries between ACS crowd and internal populations</td>
</tr>
<tr>
<td>Motivation</td>
<td>Deep-level</td>
<td>Absolute</td>
<td>Are there a diverse set of motivations within the ACS crowd?</td>
<td>Based on the absolute number (N) of motivations</td>
</tr>
</tbody>
</table>

3.2.2 How to Derive Solver Motivations?

Motivation is a key component of deep-level diversity. In the following section, we introduce a mixed-method approach for identifying and categorizing motivations from a large dataset of raw text data, and demonstrate its use on the ACS survey data.

*Inductive Coding for Thematic Motivation Categories*

Compared to motivational data collected by other scholars such as that of Lakhani and Wolf [138], Lindenberg [151], and Acar [30], our raw data has a few differentiations. First, the participation motivations exist in a context of space robotics problem solving, which differs from the previous studies and their context for solver motivation. Secondly, the motivations data in ACS are collected by directly asking people to type out their answers in their own words in English, which is different from the traditional survey structure of the Likert scale [138][151].

In order to examine the 9000+ motivations in raw text data systematically, we adopted a mixed research method of qualitative inductive coding and natural language processing (NLP) multi-label text classification algorithm to capture the thematic categories of each motivation data.

Inductive coding is a qualitative data analysis process where the researcher reads and interprets the raw textual data, often with repetition and comparison, until important concepts, themes, or models emerge. It is often used in areas with limited theory since it does not require predetermined
identification and focus on particular variables, which might not end up being the most important
determinant of the phenomenon [152]. It is therefore fairly suitable use in our study, as we don’t have
predeterminant understanding of the motivational data, collected in raw textual data in the ACS.

We selected a subset of motivational text data (sample size n = 143) from the entry surveys as
the input text for the later NLP process. Two researchers from the lab perused the text data and noted
down the essence of the meaning for each text. They then grouped similar concepts and assigned a
theme code that describes the group. The process iterated until the theme code set were reduced to
an appropriate number [152].

In our case, there are six major thematic categories (theme codes) that emerged from the
inductive coding process on the ACS motivational data: Problem Solver, Competent, Enthusiasts,
NASA Enthusiasts, Self-starter, and Extrinsic. These six categories are consistent among the
researchers and are exhaustive enough to describe any data drawn from the motivational dataset. Since
text and sentences may convey multiple layers of information, a single motivational data might fall
under several thematic categories. For example, “being an engineer and passionate about robots from
childhood” will meet both the “Competent” and “Enthusiasts” categories. Given the entry-survey
didn’t ask each submitter to self-select one and only one primary motivation, we don’t have a basis in
the data for assigning priority. If a motivation text falls under multiple categories than it would be
triggered whenever we call any of the category. These six categories become the labels for the
supervised NLP algorithm in the next step. We will discuss each of the six categories in more details
in the results section.

*Natural Language Processing for the Distribution of Motivation Categories*

Upon receiving the labels, we then train and test on the inductive coded subset with one-
versus-rest supervised linear Support Vector Classification (SVC) [153]–[155]. We used Python as the
programming language, and the package of *scikit-learn* for the multi-label text classification in
our text data. Multi-label classification assigns to each sample (i.e. motivational data) a set of target
labels (i.e. the six motivational categories from inductive coding.) This process could be understood
as predicting properties of a data-point that are not mutually exclusive, such as topics and themes that
are relevant for a document [156]. An example would be predicting from the keywords pool for a
publication where several keywords or none of the keywords are descriptive of the publication at the
same time. The classifier of OnevsRest in *sklearn.multiclass* module allows the algorithm to
study the pattern based on the text input and then predict the binary result (0 or 1) for each of the six
categories we identified for each motivation input.

We started with data preprocessing, which includes replacing abbreviation with full expression
and removing space and unnecessary marks [155]. In another attempt of conducting unsupervised
Latent Dirichlet Allocation (LDA) for topic modelling, we applied further preprocessing for the
motivational data, which included tokenization, a process of splitting the text into sentences and
sentences into words; lemmatization, a process of transforming words in third person to first person
and verbs in past and future tense into present; and stemming words to their root form and other
processing technique [157], [158]. While topic modelling gave us some insights on the underlying
topics and their respective weights in the whole dataset, we did not choose to proceed with the
unsupervised text modeling approach. Given the research goal is to categorize and map the
unstructured text data into a set of predetermined labels from the inductive coding, we decided that
multi-label classification approach is more suitable.

Once we cleaned up the text data, we split the 143 motivations with labels from the submitters
into random train and test subsets with sklearn.train_test_split. From here, we trained several
classifiers under the OneVsRest multi-label strategy to see their respective predicting accuracy,
including Naive Bayes, LinearSVC, and Logistic Regression. Among the tested classifiers,
Linear Support Vector Classification (LinearSVC) performed slightly better than the other two
classifiers with an average test accuracy of 0.823, compared to Logistic Regression classifier being
0.799 and Naïve Bayes being 0.801. Therefore, we chose LinearSVC as the classifier to apply onto the
larger dataset of over 9000+ motivations from ACS registrants.

After applying the classification algorithm to the larger dataset, we compare the predicted
binary result against the inductive coded result for each category. The average prediction accuracy rate
is 82.64% across motivational categories, meaning the algorithm is able to “read” the motivation and
predict whether it belongs to a certain category 82 times correctly out of 100 attempts. For each
motivation data, we also check whether the algorithm is able to predict at least one of the categories
correctly against the inductive coded results. The accuracy here is 79.17%. In the large motivation
dataset, we randomly select 3 groups of 50 motivations and apply similar accuracy checks. We receive
categorical accuracy rate of 78.73% and motivational accuracy rate of 69.74% through this accuracy
checking approach. We think these results are significant enough to reveal the general trends of the
motivations and assist us in answering the questions we wish to answer. Figure 3.3 presents a
visualization of the process.
3.2.3 How to Probe the Relationship Between Diversity and Solution Quality?

The second research question of this thesis takes a step towards understanding the relationship between diversity and innovation in open innovation. In the context of ACS, this translates into studying the relationship between diversity attributes and the solution quality of the ACS crowd.

What is the Relationship between Diversity and Solution Quality?

To address this question, we propose a two-step approach. In the first step, we investigate the yield of quality solutions for each diversity dimension. We compute the yield based on the fraction of mixed detailed solutions among all of the submissions. The yield is based on simple descriptive statistics and allows to establish an initial understanding that informs further hypotheses formulation regarding which diversity attributes lead to quality solutions.

In the second step, we employ statistical methods of one-way ANOVA and Tukey multiple pairwise comparison tests to investigate the statistical significance of these diversity features on leading to quality solutions [160], [161]. For each of the tests, we use the yield as a dependent variable and consider the diversity features as independent variables to statistically investigate their relationship.

The individual roles of each statistical test are as the following. One-way ANOVA is an extension of the independent two-sample-t-test for comparing means in a dataset where there are more than two groups of categorical variables. For the categorical independent variables that are deemed statistically significant by the one-way ANOVA, we can then apply Tukey Honest Significant Differences (HSD) test, which is a post-hoc process for performing multiple pairwise-comparison
between the means of group [160]. The results of the Tukey HSD indicate on average, how much the levels of a categorical variable differ from each other. We choose these two complementary methods to understand if one or more of the diversity attributes have a significantly higher yield of quality solutions. Thus, the proposed methodology allows to understand which diversity features are more influential in terms of leading to quality solutions, providing the much-needed connection to government STEM policy objectives and the theory of Open Innovation.
Chapter 4 Results and Discussion

In this section we present the results to the research questions posted in Chapter 1, employing the methodologies discussed in Chapter 3. Section 4.1 addresses the first research question: to what extent is the ACS crowd diverse? To address RQ1, we consider diversity from the perspectives of deep vs. surface level, individual vs. population, and relative vs. absolute level, with respective analysis methods to derive insights on the ACS diversity performance. Section 4.2 focuses on the second research question, by isolating the subset of participants who submitted quality solutions and investigating which diversity features are influencing these contributions.

4.1 To what extent is the ACS crowd diverse?

In this section, we will address the first research question of this thesis: to what extent have federal prize competitions reached a diverse population to satisfy the diversity objectives in STEM fields?

4.1.1 To what extent is the ACS crowd diverse on surface level attributes?

Recalling Section 2.1.2, surface diversity refers to attributes that are relatively easy to observe, such as demographic information of gender, age, and country of origin. Subsection 4.1.1 focuses on studying the surface level attributes among the ACS crowd, through the lenses of absolute, population, or relative diversity dependent on the appropriate context.

4.1.1.1 Gender Diversity

Many STEM federal agencies have identified increasing the presentation of females in their organization as a specific diversity goal. According to NASA, their Special Emphasis Programs (SEP) “focus special attention on groups that are conspicuously absent or underrepresented in a specific occupational category or grade level in the agency's work force.” One of the programs is designed specifically for women, along with eight other groups [38]. Similarly, HHS also have a Special Emphasis Program to ensure equal employment opportunity for women [43].
In recent years, agencies have increased their engagement with open innovation challenges, with the expectation that they will achieve diversity of solvers [23], [114], a key assumption being that these challenges will level the playing field for all, therefore encouraging more females to participate in the traditionally male-dominated STEM fields.

Given this, reaching females through open innovation challenge is considered as an “absolute diversity” goal in this thesis. The relevant policy question for evaluating the ACS crowd from this perspective therefore becomes: *Is the ACS crowd made up of more females than the internal solvers?*

To answer this question, we first compare the ACS submitters’ gender ratio to that of the internal reference population. Recalling that submitters are a subset of registrants who provide quality solutions, therefore, their capability and skills are more closely comparable with the reference populations than the registrants.

Within the NASA S&E Full-time employees, there are 76.9% of males. Among the US Aerospace Workforce, the male ratio is 74.7%. Noted this is a population that represents the aerospace workforce strictly, while the ACS crowd is not a population with only aerospace-related population. In comparison, the male representation in the ACS submitters is as high as 90.4%, leaving less than 10% of participation from females – a more drastic underrepresentation of females than both reference populations. Since we observed a much large gender gap in ACS quality solution submitters than the reference populations, which is the reverse of the absolute diversity goal, we decided to enlarge the pool a bit by looking into the ACS registrants. See Figure 4.1 for the gender ratio comparison across the population.

![Figure 4.1 Gender Ratio Comparison Across Populations](image-url)
Compared to the submitters, the registrants are those who showed general interest in solving a robotics problem. It is a much larger group in number, as well as a group defined more by their interest than by their capacity. Replicating the comparison above, the registrant data also reveals a male ratio higher than those of the reference populations, at 85.7%. See Table 4.1 for details on the gender diversity comparison across populations.

Table 4.1 Comparison and Coefficient of Unalikability on Gender

<table>
<thead>
<tr>
<th>Gender Categories</th>
<th>ACS Registrants</th>
<th>ACS Quality Submitters</th>
<th>NASA S&amp;E Full-Time Workforce</th>
<th>Data USA Aerospace Workforce</th>
<th>ACS Registrants</th>
<th>ACS Quality Submitters</th>
<th>NASA […] Workforce</th>
<th>[…] Aerospace Workforce</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>7,780</td>
<td>75</td>
<td>8,261</td>
<td>61,119</td>
<td>85.7%</td>
<td>90.4%</td>
<td>76.9%</td>
<td>74.7%</td>
</tr>
<tr>
<td>Female</td>
<td>1,301</td>
<td>8</td>
<td>2,482</td>
<td>20,720</td>
<td>14.3%</td>
<td>9.6%</td>
<td>23.1%</td>
<td>25.3%</td>
</tr>
<tr>
<td>Total</td>
<td>9,081</td>
<td>83</td>
<td>10,743</td>
<td>81,839</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

The results above indicate that when broadcasting a complex space engineering problem to a large crowd, such as the members on freelancer.com, the absolute gender diversity objective is not necessarily achieved. In fact, the descriptive statistics indicate that gender diversity in this case (ACS) is even worse than the traditional problem-solving space (NASA internal S&E workforce). Furthermore, the ACS quality solution submitters are even less diverse, in terms of female representation, than the ACS registrants who show general interest to the problems.

Studies have shown that, in incentive tournaments, women are more likely to shy away from competition than men despite having the same abilities [142]. In ACS, an open innovation challenge structured as an incentive tournament, there is a similar lack of female representation when compared to the internal solvers at NASA. It is therefore a strong support to the previous work [142]. From the low turnout rates in both registrants and submitters, it was not effective in both attracting and maintaining female participation. For federal agencies that wish to achieve the gender diversity goal, unfortunately, this study concludes that the current approach to ACS and similar open innovation challenges are not the most effective approach.

Due to the scope, this thesis does not know or show why there might be such absence of women. There exist some theories attempting to explain, such as women might systematically self-evaluate as less competent and withdraw from competition [141], [142]. However, future research is needed to explain such absence, potentially through the studies on motivation between female ACS
registrants and submitters to first understand whether incentive difference drives involvement difference.

4.1.1.2 Age Diversity

Regarding age diversity in open innovation challenges, there are many assumptions and objectives raised by different organizations.

One of them is the absolute diversity objective in reaching a younger population through open innovation. As discussed earlier, there exists a demographic “cliff” in age among many federal agencies [117]. By introducing a younger population into the organization through open innovation challenge, it is likely to alleviate some of the negative impacts resulting from the age “cliff” [118]. For STEM public agencies, engaging with the younger population is also an enhancement to their STEM education agenda [162], [163]. Therefore, one policy question regarding age is: Is the ACS crowd younger than the internal solver?

Some organizations engaging with open innovation have recognized two undervalued strategic resources for generating innovative concepts: young talents who are too young to enter the labor market and old talents who have retired and left the regular employment market [164]. Some assume these two populations are widely presenting in open innovation challenges as both populations are outside of the traditional labor market, therefore having relatively more free time to participate [164]. Therefore, in addition to ask whether there are more younger people in the ACS, we also ask a second absolute diversity question: Is the ACS crowd also older than the internal solver?

Another policy question is from the population diversity perspective. In particular, we ask: has the ACS reached a more even age distribution than that of the internal workforce?

Starting with the absolute diversity questions, we compare the median age between the ACS crowd and the NASA S&E full-time employees to see whether the former skew towards a younger population. The median age for both ACS registrants and quality solution submitters is between 25-34, while that for the NASA population is 45 and above. While there are only less than 10% of the ACS crowd who are over 45 years old, we observe a significant dominance of NASA S&E engineering workforce (66.6%) in the same age range. We then perform a Fisher Chi-square test to confirm the two age distributions are statistically significantly different from each other. Our data shows that ACS does achieve a younger population than the internal solvers, supporting the absolute diversity goals held by many federal agencies [162], [163]. However, since the ACS does not reach more older
population when compared to the internal workforce, it does not tap into the “undervalued strategic resources of old talents who have retired and left the regular employment market” [164]. Figure 4.2 shows the age distribution comparison between the populations. Table 4.2 further demonstrates the differences.

To address the age diversity question from a population diversity perspective, we resort to the unlikability score. We calculate the respective unlikability score for each reference population. Table 4.2 shows the results for ACS Registrants, ACS quality solution submitters and NASA S&E workforce. Among the three populations, ACS submitters is the most diverse in terms of age composition, with a unlikability score of 0.691, followed by the ACS registrants at 0.675, and lastly, the NASA employees at 0.502. There is a 38% difference between the ACS submitters and the NASA workforce, with the ACS submitters showing more heterogeneity than the ACS registrants and internal solvers. Therefore, the ACS crowd is more diverse than the NASA S&E workforce in terms of age population diversity.
### Table 4.2 Comparison and Coefficient of Unalikeability on Age

<table>
<thead>
<tr>
<th>Age</th>
<th>ACS Registrants</th>
<th>ACS Submitters</th>
<th>NASA S&amp;E Full-Time Workforce</th>
<th>ACS Registrants</th>
<th>ACS Submitters</th>
<th>NASA S&amp;E Full-Time Workforce</th>
</tr>
</thead>
<tbody>
<tr>
<td>18-24</td>
<td>3172</td>
<td>22</td>
<td>101</td>
<td>36.3%</td>
<td>25.9%</td>
<td>0.9%</td>
</tr>
<tr>
<td>25-34</td>
<td>3537</td>
<td>36</td>
<td>1462</td>
<td>40.5%</td>
<td>42.4%</td>
<td>13.6%</td>
</tr>
<tr>
<td>35-44</td>
<td>1328</td>
<td>20</td>
<td>2026</td>
<td>15.2%</td>
<td>23.5%</td>
<td>18.9%</td>
</tr>
<tr>
<td>45 and up</td>
<td>702</td>
<td>7</td>
<td>7154</td>
<td>8.0%</td>
<td>8.2%</td>
<td>66.6%</td>
</tr>
<tr>
<td>Total</td>
<td>8739</td>
<td>85</td>
<td>10743</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
</tr>
<tr>
<td>Coefficient of Unalikeability</td>
<td>0.675</td>
<td>0.691</td>
<td>0.502</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Our study concludes that ACS indeed attracts a younger and more even population than the internal solvers. It does not attract more older population to solve a robotics design problem. Some federal agencies report having an aging workforce [117], therefore, the younger crowd reached in open innovation challenges could potentially introduce new perspectives to and create synergy with the internal workforce [164], for both educational and innovative benefits.

#### 4.1.1.3 Country diversity

Dependent on the contracting authorities, federal prize challenges participants are subject to different citizenship restrictions. For example, the COMPETES Act limits the participation of federally funded prize-based contests to only U.S. citizens [165]. However, the ACS in our study falls under an alternative contracting authority. It is organized as part of the NASA Tournament Lab, which follows the Federal Acquisition Regulation (FAR) contract outlined within the March 2010 OMB Memo [166], [167]. Under the FAR contracting mechanism, the ACS does not restrict its participants to U.S. citizens only. Despite the fact that various contracting mechanisms exist and each outlines differently on citizenship [165], [167], it remains a debate among federal agencies as whether to “opened up” their future prize competitions to foreign participation [166].

In our selected agencies, there also exists divergent opinions on whether a global crowd should be a diversity objective in open innovation or not. According to NSF, who holds a more protectionist perspective on this issue, “it is appropriate to restrict participation to U.S.-incorporated or chartered entities and teams led by U.S. citizens or permanent residents,” given one of the purposes of a prize program is to “strengthen U.S. innovative capacity”[168]. On the other hand, organizations like NASA has increasingly collaborated with “a more diverse set of entities in the broader national and
international citizenry,” with a hope to “inspire further efforts to feature the world’s people in our work of innovation and discovery — and to show individuals and groups from around the world the value of their participation with NASA, encouraging them to join us in the pursuit of knowledge, innovation, and exploration” [169].

Since the ACS is launched freelancer.com as a NASA Tournament Lab sponsored challenge, a global audience have relatively easy access to its information. Therefore, our data provides the unique insights on where ideas and crowds come from should an open innovation challenge be “opened up” to a global audience.

Since NASA employees are subject to strict US nationality restriction, by definition, the ACS crowd is more diverse than NASA employees in terms of the number of countries reached. However, there are two remaining policy questions we set to answer in this section, the first one focuses on the population diversity of the ACS crowd when compared to the US Robotics workforce. This is an alternative reference population who are also capable of the solving the tasks and are subject to looser nationality restrictions than NASA employees. Therefore, we ask: has the ACS reached a more even country distribution than that of the reference workforce?

To answer this question, we look at the scores of unalikeability for countries and regions represented in both populations. In the registration survey, we ask each ACS participant to identify the country that they currently reside in. In total, there are 147 residency countries reported by the registrants. The US robotics workforce is asked for their birth countries; therefore, the data is collected slightly differently from that of the ACS crowd. Noting the nuances of the two data collection processes, we proceed with our analysis.

From Table 4.3, we see that the ACS registrants show higher heterogeneity with higher scores of unalikeability in both country and region representation than that of the US Robotics workforce (country: $u = 0.923$ vs. $u = 0.855$; region: $u = 0.668$ vs $u = 0.56$). It shows that ACS is more diverse on a population perspective than the US robotics workforce. In a more detailed region breakdown, we observe a few interesting insights.
Table 4.3 Region and Country Composition and Coefficient of Unalikeability Across Populations

<table>
<thead>
<tr>
<th>Region</th>
<th>Astrobee Registrants</th>
<th>US Robotics Workforce</th>
<th>Astrobee Registrants (%)</th>
<th>US Robotics (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asia</td>
<td>4,500</td>
<td>957,012</td>
<td>48.8%</td>
<td>62.2%</td>
</tr>
<tr>
<td>Americas</td>
<td>2,201</td>
<td>280,880</td>
<td>23.9%</td>
<td>18.3%</td>
</tr>
<tr>
<td>Europe</td>
<td>1,502</td>
<td>197,750</td>
<td>16.3%</td>
<td>12.9%</td>
</tr>
<tr>
<td>Africa</td>
<td>904</td>
<td>63,175</td>
<td>9.8%</td>
<td>4.1%</td>
</tr>
<tr>
<td>Oceania</td>
<td>106</td>
<td>9,055</td>
<td>1.2%</td>
<td>0.6%</td>
</tr>
<tr>
<td>NA</td>
<td>2</td>
<td>29,544</td>
<td>0.0%</td>
<td>1.9%</td>
</tr>
<tr>
<td>Total</td>
<td>9,215</td>
<td>1,537,416</td>
<td>100.0%</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Coefficient of Unalikeability (Region) 0.668

Coefficient of Unalikeability (Country) 0.923

In Figure 4.3, Southern Asia (the region that contains Afghanistan, Bangladesh, Bhutan, India, the Maldives, Nepal, Pakistan, and Sri Lanka) contribute the most ACS registrants and US robotics workers. This is not surprising as Southern Asia is one of the most populated regions in the world [170]. In most other regions, the ACS crowd is demonstrating more diverse representation than the reference population except in regions of South Eastern Asia, Eastern Asia, Caribbean, and Central America. In these regions, particularly in Eastern Asia (China, Hong Kong, Macau, Japan, Mongolia, North Korea, South Korea, and Taiwan), there are more representation in the US robotics workforce (over 15%) but less so in the ACS crowd (less than 5%). These regional differences intrigue us to delve deeper into the country level to understand what might explain them.
In terms of the country representation, as shown in Figure 4.4, India out-represents other countries of residency in both the ACS (24%) and US Robotics and Automation workforce (35%). China is the second leading country in the US robotics workforce but outside of the top 20 in ACS crowd. One possible reason might be that freelancer.com is not widely accessible or known in China, therefore hindering the participation from the country. Alternative explanation might be an individualized express of “techno-nationalism” [171] from capable solvers in China, where they withdraw from contributing to a US federal-agency sponsored robotics challenge as a way to convey nationalism. Future work on the audience base and past nationality participation track record might help explain this phenomenon better.

Figure 4.4 Top Countries Represented in ACS Registrants

A follow-up question to the above observation is: whether ACS has reached a different population than what is represented in the global robotics industry?

To answer this question, we compare the ACS country ranking to the global robotics industry development ranking to check whether there exists overlap. The data we use as a proxy to the robotics industry development level is the national robotics adoption rate per 10,000 manufacturing workforces in 2017 [172]. Figure 4.5 shows the top countries of robotics adoption rates. To our surprise, none of the top 6 countries with the highest robotics development level (Korea, Singapore, Germany, Japan, Sweden) is present in the top 19 countries of the ACS crowd. On the other hand, countries such as Pakistan, Egypt, Bangladesh, Indonesia, Turkey, Brazil contribute rather significant number of registrants to the ACS, but they are ranked pretty low in the national robotics adoption ranking.
Figure 4.5 Robots per 10,000 manufacturing workers, 2017 [172]

The results above indicate that open innovation challenges like the ACS are tapping into talents from countries that are not traditionally known or thought-of for robotics solutions. In many cases, these countries have only a developing or an emerging robotics industry. However, residents in those countries could still be interested and capable of solving a complex space robotics problem. We suspect their participation might be a mix result of competency demonstration, capacity building, or seeking a source of monetary income through the gig economy via open innovation challenges.

In relation to the policy debate in the beginning of this section, these results suggest that, if a prize challenge is opened up for global participation, there are indeed “value of individuals and groups from around the world” [169]. By comparing the nations of origin among the ACS solvers to the developed robotics countries, where solutions are typically expected from, we learn that some unexpected locations with only developing robotics industries can still produce quality solutions.

4.1.2 To what extent is the ACS crowd diverse on deep-level attributes?

Subsection 4.1.2 studies deep level diversity features such as the crowd’ education background, career fields and motivations. These features are generally latent and unobservable by appearance. However, a closer look at these attributes will help us understand whether open innovation challenges achieve deep-level diversity.
4.1.2.1 Work Experience Diversity

In their diversity and open innovation documents, many federal agencies stress the goal to reach a diverse set of life experience, in terms of work experience, skills, and technical expertise, from the crowd via prize challenges [24], [37], [114]. For example, NASA suggests that it “need individuals from a wide variety of backgrounds, skills, and abilities that can bring unique perspectives, and life experiences, to tackle highly complex challenges to achieve NASA’s mission”[37]. Similarly, DOE mentions that as a “as a science and technology agency, it has unique diversity characteristics that must be addressed… such as diversity of thought, technical expertise, and life experiences […] Prizes may be appropriate for use when: […] bring out-of-discipline perspectives to bear”[24]. Furthermore, NSF suggests that one of the evaluation strategies on prize challenge could be checking whether “whether the program is attracting large numbers of contestants more diverse than NSF’s largely academic constituency” [168]. There is a policy intention for organizations to use prize challenges as a tool to reach a different solver base than their internal workforce, or the stakeholders they typically interact with.

Based on this, we formulate the first policy question from an absolute diversity perspective: 
*is the ACS crowd representing more career fields than the internal solvers?*

On top of measuring the fields of career experience among the crowd, a second policy question is posed relating to the years of experience they have. Measuring the time is another angle to study whether the ACS crowd have different career experience than the internal solvers.

As discussed earlier, there is an age “cliff” within the federal workforce. Roughly one-third of the federal employees onboarded at the beginning of FY2019 will be eligible for retirement by the end of FY2023 [117]. Similar to this age composition, the work experience measured by years also skew towards seniority among the federal workforce. For example, the median work experience for NASA employees is between 15-19 years and there are nearly 40% of NASA employees reporting work experience of more than 25 years.

In light of this, many federal agencies explicitly mention reaching young professionals, who by definition, have less work experience and technical experience, as a goal in their open innovation and diversity strategies. For example, NASA has set up a Special Emphasis Program for young professionals [38]. NSF also define one of their “near-term impact” of prize program being “attracting diverse participants in the competition, involving students and young professionals ”[168].
Given the above discussion, we form two additional policy questions that speak to this context, one from absolute diversity perspective while the other from population diversity: *Is the ACS crowd differ from the internal solvers by having less work experience? Is the ACS crowd more diverse in terms of evenness on work experience?*

To address the first working question, we analyze the represented career fields among the ACS crowd. In the ACS registration survey, participants were asked about the disciplines and fields that they had previously worked in. Among the 9,215 registrants, 3,489 (37.8%) of them reported with only one previous career field, while the remaining majority of 5,724 registrants (62.1%) reported with more than one fields, indicating more than half of the group have multidisciplinary work experience. Next, we look at the reported field distribution among the ACS crowd, particularly with an interest in separating the STEM and non-STEM related fields. Figure 4.6 shows the results.

We see that among the ACS crowd, there is a wide representation of both STEM and non-STEM fields. Given that ACS seeks solutions on complex space robotics problems, it is rather surprising to see participants with experience in distant fields such as medicine, law, art, education, as well as business and finance. Compared to the internal workforce of NASA Science and Engineering employees, there are clearly broader work fields represented among the ACS crowd. This shows that the ACS achieves the absolute diversity goal of tapping into a broader range of work experience diversity defined by career fields and technical expertise.

Figure 4.6 Distribution of Career Fields Reported by the ACS crowd
The second question focuses more on the experience level, measured by years of experience reported by the ACS crowd and the internal solvers.

The ACS registration survey asked the crowd to report their number of years of experience, if any, in each area of specialization within a technical organization. As a comparison for the internal workforce, we use the years of serving time for people in NASA S&E function from the WICN dataset. Both datasets measure the length of technical experience by years and are in a five-year step range.

From an absolute diversity point of view, the majority of ACS registrants and submitters report having less than 5 years of work experience in a technical organization (75.5% & 61.2%). As a comparison, only 13.1% of the NASA science and engineering workforce fall under the same category. The median years of experience for the NASA population is between 15-19 years, while that for the ACS crowd is under 5 years. While there are a significant proportion of NASA workforce reporting work experience of longer than 25 years (37.8%), that ratio is only 1.6% for the ACS registrants and 1.2% for the quality submitters. We observe that the ACS crowd achieves the absolute diversity goal in reaching more young professional than the internal workforce, who are defined as having less technical experience.

From a population diversity standpoint, the NASA S&E workforce has a higher degree of heterogeneity in their represented years of experience, measured by a higher value of unalikeability at 0.869 than that of the ACS submitters (\(u = 0.577\)) and the ACS registrants (\(u = 0.410\)) This shows that the NASA workforce is more evenly distributed in terms of their technical expertise than the ACS crowd. This is because the ACS crowd is highly skewed towards having “under 5 years of experience.” There are 75.5% of registrants and 61.2% of submitters reported in that range. Such concentration explains the unevenness of experience distribution among the ACS crowd. See Table 4.4 for details.
### Table 4.4 Comparison on Technical Experience and Coefficient of Unalikeability

<table>
<thead>
<tr>
<th>Years of Experience Categories</th>
<th>ACS Registrants</th>
<th>ACS Submitters</th>
<th>NASA S&amp;E Full-Time Workforce</th>
<th>ACS Registrants</th>
<th>ACS Submitters</th>
<th>NASA S&amp;E Full-Time Workforce</th>
</tr>
</thead>
<tbody>
<tr>
<td>Under 5</td>
<td>6,955</td>
<td>52</td>
<td>1,405</td>
<td>75.5%</td>
<td>61.2%</td>
<td>13.1%</td>
</tr>
<tr>
<td>5 to 9</td>
<td>1,169</td>
<td>16</td>
<td>1,401</td>
<td>12.7%</td>
<td>18.8%</td>
<td>13.0%</td>
</tr>
<tr>
<td>10 to 14</td>
<td>526</td>
<td>8</td>
<td>1,733</td>
<td>5.7%</td>
<td>9.4%</td>
<td>16.1%</td>
</tr>
<tr>
<td>15 to 19</td>
<td>224</td>
<td>5</td>
<td>1,493</td>
<td>2.4%</td>
<td>5.9%</td>
<td>13.9%</td>
</tr>
<tr>
<td>20 to 24</td>
<td>189</td>
<td>3</td>
<td>655</td>
<td>2.1%</td>
<td>3.5%</td>
<td>6.1%</td>
</tr>
<tr>
<td>25 to 29</td>
<td>71</td>
<td>1</td>
<td>1,433</td>
<td>0.8%</td>
<td>1.2%</td>
<td>13.3%</td>
</tr>
<tr>
<td>30 to 34</td>
<td>60</td>
<td>0</td>
<td>1,734</td>
<td>0.7%</td>
<td>0.0%</td>
<td>16.1%</td>
</tr>
<tr>
<td>35 to 39</td>
<td>12</td>
<td>0</td>
<td>673</td>
<td>0.1%</td>
<td>0.0%</td>
<td>6.3%</td>
</tr>
<tr>
<td>40 or more</td>
<td>7</td>
<td>0</td>
<td>216</td>
<td>0.1%</td>
<td>0.0%</td>
<td>2.0%</td>
</tr>
<tr>
<td>Full-Time Permanent</td>
<td>9,213</td>
<td>85</td>
<td>10,743</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

| Coefficient of Unalikeability | 0.410         | 0.577          | 0.869                       |

Regarding the earlier questions, we find evidence to support that ACS is indeed more diverse than the internal NASA S&E employees by including a broader range of work experience, particularly by attracting more people with non-STEM backgrounds. The ACS also achieve the absolute diversity goal in reaching a population of young professional, who by definition possess less work experience. However, given the high concentration of people with less than 5 years of experience, the ACS crowd is less diverse than the internal workforce in terms of the evenness of the distribution.

#### 4.1.2.2 Education Background Diversity

Similar to work experience, some federal agencies expect open innovation challenges to enable them to reach a crowd with different education backgrounds than their own, or their typical stakeholders. For example, in their open innovation strategy, NSF suggests that open innovation are likely to attract “an array of individuals and organizations that is somewhat different from the scholars and academic institutions that typically apply for NSF grants.” This is because, unlike grant or contract program, prize challenges “impose fewer demands on contestants by reducing or eliminating the requirement for ex ante demonstration of the capability to succeed and by eliminating the administrative burden of accounting for expenditure of public funds” [168].
Based on this context, we formulate two policy questions. Considering that the NASA S&E workforce and the typical NSF grant contestants are rather highly educated, the first question asks from an absolute diversity perspective: *Is the ACS crowd less educated than the internal crowd?* The second question seeks to understand the education background of the ACS crowd from the population diversity angle. It asks: *Is the ACS crowd more diverse measured by the coefficient of unalikeability on education background?*

In the registration survey, we asked the ACS crowds to report their educational background by indicating all of the degrees and certificates they had obtained. We then explored similar quantitative measures from the reference populations given data availability. In this case, we choose the educational attainment data from the US Robotics and Automation workforce as the reference data.

Answering the first question on absolute diversity, the US Robotics and Automation workforce has a higher proportion of Master’s Degrees than the ACS registrants (33.2% vs 25.71%). The proportion in Doctorate degrees is also higher among US Robotics and Automation workforce than in the ACS registrants (5.3% vs. 3.01%). Figure 4.7 shows the comparison. On the other hand, the proportion of the Bachelor’s degrees (the lowest education level in the three comparable options) is higher among the ACS crowd than the reference population. These findings indicate that the ACS crowd is indeed more diverse by attracting a population with less advanced degrees than the internal workforce. Many of these crowd, despite their lower education levels, are still capable of solving the same problems.

Figure 4.7 Education Comparison Between ACS Crowd and Internal Solvers
From a population diversity perspective, the ACS crowd is not as diverse in terms of the heterogeneity in education composition as the reference population. The coefficients of unalikeability reveal that the US robotics workforce (u = 0.509) has a more heterogeneous population diversity on educational attainment than the ACS submitters (u = 0.435), than the ACS registrants (u = 0.425.) Table 4.5 shows the results.

Table 4.5 Comparison on Education Degrees and Coefficient of Unalikeability

<table>
<thead>
<tr>
<th>Education Field Categories</th>
<th>ACS Registrants</th>
<th>ACS Submitters</th>
<th>Data USA Robotics and Automation Engineer</th>
<th>ACS Registrants (%)</th>
<th>ACS Submitters (%)</th>
<th>Data USA Robotics Engineer (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bachelor's degree</td>
<td>4,195</td>
<td>45</td>
<td>2,429,925</td>
<td>71.3%</td>
<td>69.2%</td>
<td>61.5%</td>
</tr>
<tr>
<td>Master's degree</td>
<td>1,513</td>
<td>19</td>
<td>1,309,914</td>
<td>25.7%</td>
<td>29.2%</td>
<td>33.2%</td>
</tr>
<tr>
<td>Doctorate degree</td>
<td>177</td>
<td>1</td>
<td>209,315</td>
<td>3.0%</td>
<td>1.5%</td>
<td>5.3%</td>
</tr>
<tr>
<td>Total</td>
<td>5,885</td>
<td>65</td>
<td>5,949,154</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Coefficient of Unalikeability: 0.425 0.435 0.509

These results support the expectation of NSF, in that prize challenges indeed help achieve a population that is different from the typical grant and contract holders, when viewed from an education attainment level perspective. More people with lower education levels show up from the crowd in the prize challenges, and many of them are still capable of solving the problems.

4.1.2.3 Motivation Diversity

As a key component of deep-level diversity, motivation offers insights into why participants are drawn to open innovation challenges. Studying crowd motivation for participating is not only helpful in revealing their profile, but also instrumental in understanding the underlying mechanism of open innovation.

Inductive coding results: 6 motivation types

Recalling from earlier section, I adopted a mixed research method of qualitative inductive coding and natural language processing (NLP) multi label text classification algorithm to capture the
thematic categories of each motivation data. Below in Table 4.6 are the six categories derived through the inductive coding process.

Table 4.6 Inductive coding results

<table>
<thead>
<tr>
<th>Category</th>
<th>Explanation</th>
<th>Exemplary motivation for each category</th>
</tr>
</thead>
</table>
| Problem solver  | Motivations describe their wish to solve a problem and/or to contribute to a problem with a larger impact | “I want to do something to help humanity”  
“...technology and unification as a species” |
| Competent       | Motivations describe their capability to solve the problems                  | As a mechatronics engineer, I would like to challenge this contest  
“Our team have the similar completed project at background” |
| Enthusiasts     | Motivations describe their enthusiasm for space and/or STEM and/or challenges | “I am very passionate about robotics application of robotics in space exploration is even more exciting”  
“I love innovation” |
| Self-starters   | Motivations describe internalized incentives such as learning or proving myself | “I have desperate need of an assignment to explore extend my limits” |
| Extrinsic       | Motivations describe their extrinsic incentives such as prize money, professional credibility, or social benefits of meeting others | “I wish to join NASA so take this opportunity to get my success.”  
“I need work”  
“Because of the money” |
| NASA enthusiasts| Motivations indicates their main reason for joining is for NASA              | “It is NASA.”  
“Because I love all NASA parts of science” |

Compared to prior literature, our six categories roughly map to those discussed in literature but represent a higher resolution of specificity. Table 4.7 shows the comparison. The specification in our motivation categories suggest that each ACS crowd were driven by a diverse set of motivations compared to previous literature.
Table 4.7 Category Comparison to Literature

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Problem solver</td>
<td>Guts</td>
<td>Enjoyment-based intrinsic motivation</td>
<td>Intrinsic motivation</td>
</tr>
<tr>
<td>Competent</td>
<td>Guts / Goal</td>
<td>Obligation/community based intrinsic motivation</td>
<td>Prosocial motivation</td>
</tr>
<tr>
<td>Enthusiasts</td>
<td>Goal</td>
<td>Enjoyment-based intrinsic motivation</td>
<td>Intrinsic motivation</td>
</tr>
<tr>
<td>Self-starters</td>
<td>Goal</td>
<td>Obligation/community based intrinsic motivation</td>
<td>Learning motivation</td>
</tr>
<tr>
<td>Extrinsic</td>
<td>Gold/ Glory</td>
<td>Extrinsic motivations</td>
<td>Extrinsic motivation &amp; Prosocial motivation</td>
</tr>
<tr>
<td>NASA Enthusiasts</td>
<td>Goal</td>
<td>Enjoyment-based intrinsic motivation</td>
<td>Intrinsic motivation</td>
</tr>
</tbody>
</table>

NLP results: the distribution of motivations

Once we obtain the predicted categories for each motivation and their distribution, we see several categories dominating whiles others less represented. As shown in Figure 4.8, among those dominating categories are “Competent” and “Enthusiasts.”

We also observe surprisingly low representation in “Extrinsic” motivation (3.32% in the registered population and 4.17% in the submitted population,) which generally include the monetary, social and professional incentives that drive people to participate a prize challenge. This result is especially interesting given the context of a prized challenge where organizations explicitly set up monetary incentives in hope for broad participation.
In terms of the comparison between the ACS registrants and submitters, we observe relatively consistent proportion in the categories of “Problem solver”, “Enthusiasts”, “Self-starters”, “Extrinsic”, and “NASA Enthusiasts”. However, we see a substantial difference in the category of “Competent” between the two populations (60.41% vs. 37.62%). We suspect such gap might be a result of the drop-out of those who self-perceived as incompetent after seeing the problem statement upon finishing the registration survey. Figure 4.8 demonstrates the proportion of each category in both the submitted and registered population.

Our study provides a few points of departure from the previous work. Firstly, unlike the traditional motivational data collection approach of using Likert scales [138], [151], we ask for open-ended questions that allow for raw data input based on the own words of the participants. This rich and new data format allows us to conduct an inductive analysis, rather than the usual deductive approaches that relies on forecasted solvers’ motivations [138], [151]. It gives us more *ex post* and nuanced understanding, grouped in a more specific categorization compared to the existing studies [30], [138], [139]. Based on this, we employed a unique approach by combining the inductive coding and the NLP analysis, which presents further insights on the distribution of the motivation. Secondly, compared to motivational data analyzed by scholars such as Lakhani and Wolf [140], Lindenberg [151], and Acar [30], our data captures motivations in a space context as a result of how NASA and Freelancer broadcast and publicize the challenge series. Despite so, the identified motivations still largely overlapped and can be generalized for future motivational studies.
4.1.3 Key Takeaways for RQ1: To what extent have ACS achieved diversity?

The short answer to this question is “yes, ACS has achieved diversity, but…” Through our analysis, we learn that open innovation challenges like the ACS do not reach all types of diversity, in terms of dimension or feature, all the time.

Wrapping up the analysis on surface diversity features of gender, age, and country of residence, we reach a rather complicated conclusion. On gender, the ACS crowd is not as diverse, in fact, less diverse than the internal solvers at NASA, in terms of female representation. This result and the followed discussions in section 4.1.1.1 indicate that an open innovation challenge might not be the best tool for increasing female diversity in agencies. Women might be shying away from competition than men despite having the same abilities, in incentive tournaments like the ACS [142]. Regarding age, the findings show that ACS reaching a younger and more even age profile of crowd than the internal solvers facing the same problem. For agencies that face an age “cliff” and seek input from a different age group, these findings provide positive signals. However, ACS does not reach an older population as some have expected, challenging the assumption that prize challenges attract the younger and the older talents because they are out of the traditional labor market and have more time [164]. In terms of country of residence, ACS is useful in reaching talents around the world, largely attributed to its nature of broadcasting via the internet. It successfully introduces a rather exclusive space robotics engineering problem to a broad audience, many from countries that are unexpected for souring robotics solutions. The findings support that if a prize challenge is broadcast outside of the US, there are capable crowd ready to solve the problems, generating values for the sponsoring agencies. Broadly speaking, these international crowd are also contributing to the US innovation capacity through agencies. Given the above results, it shows that open innovation challenges provide access to people who want to solve a problem but generally do not know how to or have the right opportunity to do so.

On the other hand, the answers to whether ACS achieves absolute diversity goals in deep-level attributes are a consistent yes. Our data shows that ACS is effective in attracting a more diverse set of career fields than the internal workforce, with many being non-STEM related. This finding adds value to the policy discussion, suggesting that indeed, prize challenge will lead to a different and more diverse group than their typical constituency in terms of expertise domain. This new population also differ by having less work experience, fitting into the definition of “young professional,” which is a specific target group many federal polices try to empower. On the other hand, the large number of these young
professionals in the ACS crowd make the overall population less diverse from an evenness angle, measured by the coefficient of unalikeability, when compared to the internal workforce. Compared to the internal solvers, the ACS crowd also have relatively lower education attainment level, which differentiate from the internal workforce in many STEM federal agencies. Lastly, this thesis identifies a diverse set of motivations among the ACS crowd. The inductive coding and the NLP-based distribution analysis add nuances to the existing understanding on solver motivation in open innovation. The dominance of “Competent” and “Enthusiasts” and underrepresentation of “Extrinsic” motivational types hint on what and how the ACS crowd can be incentivized when participating in a prize challenge.

It is an interesting observation that the ACS achieves more absolute diversity goals in deep-level attributes than in surface level attributes. It highlights the importance to distinguish and measure diversity from multiple dimensions. The clear miss on some surface diversity attribute such as gender also suggest that organizations need to hold realistic expectations on where open innovation might and might not help addressing diversity objectives. Even though our data show failed diversity goals in some aspects, the remaining achieved diversity aspects, such as in age, country, work experience, education level are still valuable for organizations for different reasons stated above. In the next section, we focus on studying whether and where the achieved diversity features lead to quality innovation.
4.2 To what extent has achieving increased diversity led to innovative solutions?

Existing diversity policies assume that increased diversity yields improved outcomes. In this section, we investigate which diversity dimensions and features influence the likelihood of obtaining quality solutions.

4.2.1 Which diversity feature(s) matter for quality solutions to arise?

We operationalize this question by examining whether there is any significant difference between the likelihood of generating quality solutions among the subcategories (levels) of diversity features such as age, gender, education level, years of technical experience.

The one-way ANOVA test takes on independent diversity features and looks into the statistical likelihood differences among the levels of each feature in delivering a quality solution. For diversity features such as age, bachelor degree attainment, STEM field relevant experience, we observe P-values smaller than 0.05, suggesting that the levels of these features are significantly different from each other in explaining the likelihood of quality solutions. In other diversity features such as gender and years of experience, the test results are not statistically significant to explain the differences, which might be a result of the low sample size in one of the levels. Table 4.8 below presents the results for the one-way ANOVA.

This tells us that age, education, and field of experience (whether STEM or not) matter for generating quality solutions while the other features do not. Since one-way ANOVA only indicates the statistically significant difference, to understand which subcategories of diversity features have more significant impacts in over the others, we further delve into the Tukey Honest Significant Difference test.
Table 4.8 One-way ANOVA results for multiple diversity features

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

255 observations deleted due to missingness

<table>
<thead>
<tr>
<th>Diversity Feature</th>
<th>d.f.</th>
<th>Sum of Squares</th>
<th>Mean Squares</th>
<th>F value</th>
<th>Pr (&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age group</td>
<td>2</td>
<td>0.06</td>
<td>0.03098</td>
<td>3.382</td>
<td>0.03402 *</td>
</tr>
<tr>
<td>Gender</td>
<td>1</td>
<td>0.01</td>
<td>0.01376</td>
<td>1.503</td>
<td>0.22030</td>
</tr>
<tr>
<td>Bachelors or not</td>
<td>1</td>
<td>0.06</td>
<td>0.05960</td>
<td>6.507</td>
<td>0.01076 *</td>
</tr>
<tr>
<td>STEM fields or not</td>
<td>1</td>
<td>0.06</td>
<td>0.06461</td>
<td>7.053</td>
<td>0.00793 **</td>
</tr>
<tr>
<td>Max years of experience</td>
<td>47</td>
<td>0.45</td>
<td>0.00954</td>
<td>1.041</td>
<td>0.39539</td>
</tr>
<tr>
<td>Residuals</td>
<td>8907</td>
<td>81.58</td>
<td>0.00916</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4.2.1.1 Age Diversity and Solution Quality

In section 4.1.1.2, we identified that ACS reached a younger population than the NASA internal workforce, with a median age at 25-34, compared to that of the NASA internal workforce at 45+. The follow-up question then becomes, whether the achieved absolute diversity goal of younger population actually yields quality solutions?

To start, we compare the yields of quality solutions between different age subcategories in the ACS crowd and present it below in Table 4.9. The initial observation is that while ACS attracted a younger population, the yield of quality solution is rather low compared to the rest of the older ACS submitters (0% for the 13-17 age groups, 0.694% for 18-24). There is an increase of yield as age increases, until it reaches the age bucket 35-44, then the yield drops. The most productive age group is between 35-44 with a yield at 1.509%.

Table 4.9 Quality Solution Yields Across Different Age Categories

<table>
<thead>
<tr>
<th>Age Categories</th>
<th>ACS Registrants</th>
<th>ACS Submitters</th>
<th>Yield from Registrant to Quality Solution Submitter</th>
</tr>
</thead>
<tbody>
<tr>
<td>13-17</td>
<td>367</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>18-24</td>
<td>3172</td>
<td>22</td>
<td>0.694%</td>
</tr>
<tr>
<td>25-34</td>
<td>3537</td>
<td>36</td>
<td>1.018%</td>
</tr>
<tr>
<td>35-44</td>
<td>1328</td>
<td>20</td>
<td>1.506%</td>
</tr>
<tr>
<td>45 and up</td>
<td>702</td>
<td>7</td>
<td>0.997%</td>
</tr>
<tr>
<td>Total</td>
<td>8739</td>
<td>85</td>
<td>0.973%</td>
</tr>
</tbody>
</table>

To further probe the age effect on quality solution, we regroup the population by generations. While the ACS successfully achieved diversity in “Generation Z” (age between 13-24), this generation
actually shows the lowest yields of quality solution \( (y_{\text{Age: 13-17}} = 0\%, y_{\text{Age: 18-24}} = 0.694\%) \) [173]. “Generation Y” (age between 25 - 44) is another achieved diverse group, and it has the highest yield of quality solutions as a generation \( (y_{\text{Age: 25-34}} = 1.018\%; y_{\text{Age: 35-44}} = 1.506\%) \). Among “Generation X” (age above 45,) which happens to be the median generation of NASA internal workforce, the likelihood \( (y_{\text{Age: 45+}} = 0.997\%) \) falls between Generation Z and Generation Y.

To see whether the likelihood differences we observe so far are statistically significant, we run a Tukey HSD test as introduced earlier in Section 3.2.3. It turns out that the mean differences between the 5-year interval groupings are not statistically significant. See Appendix I for details. This is likely a result of the respective small sample size of each age group given the 5-year intervals.

Similarly, we run the ANOVA and the Tukey HSD test to see if there is a generational gap. Both tests indicate there indeed exist generational differences in where quality solutions arise among the ACS population. Particularly, the difference between Generation Z and Y are statistically significant (P-value = 0.03 < 0.05.) See results in Table 4.10.

<p>| Table 4.10 One-way ANOVA and Tukey HSD Results for Generation Main Difference |
|-----------------------------|-------------------------------|-------------------|---------|--------|</p>
<table>
<thead>
<tr>
<th>Generation Groups</th>
<th>d.f.</th>
<th>Sum of Squares</th>
<th>Mean Squares</th>
<th>F value</th>
<th>Pr (&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation Groups</td>
<td>2</td>
<td>0.06</td>
<td>0.0294</td>
<td>3.162</td>
<td>0.0424 *</td>
</tr>
<tr>
<td>Residuals</td>
<td>9050</td>
<td>84.14</td>
<td>0.0093</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**One-Way ANOVA Results**

**Tukey Multiple Comparisons of Mean**

95% family-wise confidence level

<table>
<thead>
<tr>
<th>Mean Differences Across Generations</th>
<th>Difference</th>
<th>Lower bound</th>
<th>Upper bound</th>
<th>P adjusted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gen Z – Gen X</td>
<td>-0.004569</td>
<td>-0.0142</td>
<td>0.0051</td>
<td>0.5080</td>
</tr>
<tr>
<td>Gen Y – Gen X</td>
<td>0.000724</td>
<td>-0.0087</td>
<td>0.0102</td>
<td>0.9823</td>
</tr>
<tr>
<td>Gen Y – Gen Z</td>
<td>0.005294</td>
<td>0.0003</td>
<td>0.0103</td>
<td>0.0346 *</td>
</tr>
</tbody>
</table>

Overall, the yield and the Tukey results suggest that the younger Generation Z and the older Generation X are less likely to produce quality solutions than Generation Y, which sits in the middle. The significance difference between Generation Y and Z suggests that seniority does matter in
explaining where quality solutions come from, perhaps given the accumulated experience that comes with age.

Given the median age of NASA internal employees is 45 and above (Generation X,) this finding suggests that while the ACS has achieved the absolute diversity goal of reaching a younger population (Generation Y and Z), not all younger population are equally likely to generate quality solutions. Nevertheless, the performance of Generation Y still supports the broad assumption that diversity leads to innovation.

4.2.1.2 Technical Experience Diversity and Solution Quality

Earlier, we learn that ACS is more diverse by reaching a less technically experienced group that differ from the NASA internal workforce.

In particular, ACS attracted a large group of newcomers in technical organizations, with reported experience of less than 5 years. However, the descriptive statistics indicate that they are less likely to generate quality solutions compared to the rest of the population \((y \text{ Experience Under 5 Years } = 0.748\%)\). This is perhaps due to their lack of experience, particularly emphasized in a context of solving a complex robotics problem.

The descriptive statistics also highlight the yield increases with the reported technical years of experience, until it hits the range of 20-24 years of experience. (See Table 4.11 row 1-4.) The group with 15-19 years of technical experience is the most likely group to generate quality solution. \((y \text{ Experience 15-19 years } = 2.232\%)\) Interestingly, they are also the median reported experience in the internal NASA workforce. While a large proportion of NASA internal workforce have technical experience longer than 30 years, we observed only a small number showing up in ACS as registrants and none in quality solutions submitters \((y \text{ Experience 40 + years } = 0\%)\).

Our findings earlier show that ACS surfaced of a large number of less experienced people, who are a diverse indicator for some federal agencies. However, they do not proceed to produce as many quality solutions as those with longer work experience. This pose an interesting contrast to the earlier discussion on age, where the younger (more diverse) population are more efficient in generating quality solutions. Since age and years of experience are two closely related topics, it suggests that the ability to provide quality solution might dependent more on the knowledge acquired through the work rather than on age itself.
Table 4.11 Quality Solution Yields Across Different Technical Experience Lengths

| Years of Experience Categories | ACS Registrants | ACS Submitters | Yield  
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Under 5</td>
<td>6955</td>
<td>52</td>
<td>0.748%</td>
</tr>
<tr>
<td>5 to 9</td>
<td>1169</td>
<td>16</td>
<td>1.369%</td>
</tr>
<tr>
<td>10 to 14</td>
<td>526</td>
<td>8</td>
<td>1.521%</td>
</tr>
<tr>
<td>15 to 19</td>
<td>224</td>
<td>5</td>
<td>2.232%</td>
</tr>
<tr>
<td>20 to 24</td>
<td>189</td>
<td>3</td>
<td>1.587%</td>
</tr>
<tr>
<td>25 to 29</td>
<td>71</td>
<td>1</td>
<td>1.408%</td>
</tr>
<tr>
<td>30 to 34</td>
<td>60</td>
<td>0</td>
<td>0.000%</td>
</tr>
<tr>
<td>35 to 39</td>
<td>12</td>
<td>0</td>
<td>0.000%</td>
</tr>
<tr>
<td>40 or more</td>
<td>7</td>
<td>0</td>
<td>0.000%</td>
</tr>
<tr>
<td>Total</td>
<td>9213</td>
<td>85</td>
<td>0.923%</td>
</tr>
</tbody>
</table>

4.2.1.3 Education Level Diversity and Solution Quality

Earlier we learn that the ACS has achieved the absolute diversity goal of reaching a population that differ on education level from the internal workforce. The ACS crowd has less advanced degrees (Master’s and PhDs) but higher proportion of bachelors’ degrees. Viewing from the descriptive statistic on yield, these people have a higher probability of generating quality solution than the previous group, but less likely than Master’s degree holders. ($y_{\text{bachelor's degree}} = 1.073\%$, $y_{\text{master's degree}} = 1.256\%$) See Table 4.12 for details.

In addition, ACS did not attract as many PhDs as the US robotics labor force do. Nevertheless, this group also has rather low yield of generating quality solutions ($y_{\text{PhD}} = 0.565\%$).

The relative low yield from the group with below high school degrees could be explained by a lack of experience and disciplinary training in solving the type of problems presented in the open innovation challenge. However, the low yield among those with PhD degrees, who have extensive training and techniques, show that the likelihood of contributing quality solution does not rise as educational level increases. This observation indicates that simple measures such as the length of training (as indicated by educational degree) is not sufficient. Additional factors such as the field of education could be playing a role in determining the likelihood of generating quality solution. Among the submitters with a PhD, there might exist a mismatch of expertise despite their long period of training. Future research should look into the educational subjects reported by the PhD groups to understand whether the low yield could be explained by a mismatch of backgrounds.
Table 4.12 Quality Solution Yields Across Different Education Attainment Levels

<table>
<thead>
<tr>
<th>Education Field Categories</th>
<th>ACS Registrants</th>
<th>ACS Submitters</th>
<th>Yield</th>
</tr>
</thead>
<tbody>
<tr>
<td>Below Highschool</td>
<td>613</td>
<td>3</td>
<td>0.489%</td>
</tr>
<tr>
<td>High School</td>
<td>2717</td>
<td>17</td>
<td>0.626%</td>
</tr>
<tr>
<td>Bachelor's degree</td>
<td>4195</td>
<td>45</td>
<td>1.073%</td>
</tr>
<tr>
<td>Master's degree</td>
<td>1513</td>
<td>19</td>
<td>1.256%</td>
</tr>
<tr>
<td>Doctorate degree</td>
<td>177</td>
<td>1</td>
<td>0.565%</td>
</tr>
<tr>
<td>Total</td>
<td>9215</td>
<td>85</td>
<td>0.922%</td>
</tr>
</tbody>
</table>

To test whether the observed differences are statistically significant, once again, we run one-way ANOVA and Tukey HSD test. We treat the likelihood of whether someone generates a quality solution as the dependent variable and the subcategories of highest education degree as independent variables. The results suggest that none of the education attainment level plays a significant role in explaining the quality solutions. It is therefore hard to access whether the achieved education diversity among the ACS crowd lead to quality innovation. See Table 4.13 below.

Table 4.13 One-way ANOVA and Tukey HSD Results for Education Degree Main Differences

| Significance codes : 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ‘ 1 |
| 613 observations deleted due to missingness |

**One-Way ANOVA Results**

|                          | d.f. | Sum of Squares | Mean Squares | F value | Pr (>|F|) |
|--------------------------|------|----------------|--------------|---------|----------|
| Highest Education Degrees| 3    | 0.05           | 0.0172       | 1.824   | 0.14     |
| Residuals                | 8598 | 81.17          | 0.0094       |         |          |

**Tukey Multiple Comparisons of Mean**

| 95% family-wise confidence level |

<table>
<thead>
<tr>
<th>Mean Differences Across Highest Education Degrees</th>
<th>Difference</th>
<th>Lower bound</th>
<th>Upper bound</th>
<th>P adjusted</th>
</tr>
</thead>
<tbody>
<tr>
<td>High School – Bachelors</td>
<td>-0.0048</td>
<td>-0.0106</td>
<td>0.0017</td>
<td>0.2419</td>
</tr>
<tr>
<td>Masters – Bachelors</td>
<td>0.0018</td>
<td>-0.0057</td>
<td>0.0093</td>
<td>0.9230</td>
</tr>
<tr>
<td>PhD – Bachelors</td>
<td>-0.0051</td>
<td>-0.0242</td>
<td>0.0141</td>
<td>0.9044</td>
</tr>
<tr>
<td>Masters – High School</td>
<td>0.0063</td>
<td>-0.0017</td>
<td>0.0143</td>
<td>0.1800</td>
</tr>
<tr>
<td>PhD – High School</td>
<td>-0.0061</td>
<td>-0.0200</td>
<td>0.0188</td>
<td>0.9998</td>
</tr>
<tr>
<td>PhD – Masters</td>
<td>-0.0069</td>
<td>-0.02674</td>
<td>0.0129</td>
<td>0.8074</td>
</tr>
</tbody>
</table>
However, if we treat whether someone has a bachelor degree or not as the independent variable, then we will see a significant difference between the groups. See Table 4.14 for details. When holding whether someone holds a Master’s or PhD degrees as independent variables, neither of the test results are significant. In fact, among the several education degrees (high school, Masters, PhDs), only bachelor degrees have a significance effect. Since holding a bachelor degree is usually a premise for having more advanced degree, the results here are inconclusive to say whether the less educated population (with only bachelor’s degrees) are more likely to generate quality solution.

Table 4.14 One-way ANOVA and Tukey HSD Results for Main Differences Between Holding a Bachelor’s Degree or Not

<table>
<thead>
<tr>
<th>One-Way ANOVA Results</th>
<th>d.f.</th>
<th>Sum of Squares</th>
<th>Mean Squares</th>
<th>F value</th>
<th>Pr (&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Holding a Bachelor's Degree or Not</td>
<td>1</td>
<td>0.07</td>
<td>0.0701</td>
<td>7.675</td>
<td>0.00561 **</td>
</tr>
<tr>
<td>Residuals</td>
<td>9213</td>
<td>84.15</td>
<td>0.0091</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Tukey Multiple Comparisons of Mean | 95% family-wise confidence level |
| Mean Differences Across Holding a Bachelor’s | Difference | Lower bound | Upper bound | P adjusted |
| Yes – No | 0.0056 | 0.0016 | 0.0096 | 0.0056 |

4.2.1.4 Gender Diversity and Solution Quality

Earlier, we find that the ACS does not engage more women in participating STEM problem solving then the internal workforce, therefore failing one of the absolute diversity goals.

The descriptive statistics reveal that the female submitters of ACS did not have a higher yield of quality solutions than males, nor the population baseline. The yield for a woman to generate quality solution in the ACS is only at 0.615%, lower than that of the average yield of the population at 0.914% and that of male at 0.964%. See Table 4.15 for details.
Table 4.15 Descriptive Statistics of Yields of Quality Solutions Across Gender

<table>
<thead>
<tr>
<th>Gender Categories</th>
<th>ACS Registrants</th>
<th>ACS Submitters</th>
<th>Yields</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>7780</td>
<td>75</td>
<td>0.964%</td>
</tr>
<tr>
<td>Female</td>
<td>1301</td>
<td>8</td>
<td>0.615%</td>
</tr>
<tr>
<td>Total</td>
<td>9081</td>
<td>83</td>
<td>0.914%</td>
</tr>
</tbody>
</table>

The Tukey HSD results indicate there is not statistically significant gap between males and females in producing quality solutions in ACS, despite the descriptive statistics suggest so. This might be a result of the limited sample size of female quality solution submitters (n = 8).

This finding adds to the already conflicting but rather scarce discussions on female performance in open innovation. Jeppesen and Lakhani suggest that being a female in a science community, with an increased societal marginality, performed significantly better than men in generating quality solutions [62]. On the other hand, Balafoutas and Sutter (2019) argue that men are significantly more often to win the tournament under uncertainty and ambiguity than women [141]. However, our result suggests that there is no significant difference in the likelihood of providing quality solutions by males or females.

4.2.1.5 Career Background Diversity and Solution Quality

While ACS was effective in attracting a broad range of career backgrounds in registrants, the quality solution submitters were mostly from STEM fields that are relevant to the proposed problem domain of ACS.

For example, aerospace and defense, the most relevant field to this space robotics challenge, have the highest probability of providing quality solutions. It is then followed by production and manufacturing, medicine, and engineering and science. (\( y_{\text{Aerospace and defense}} = 2.113\% \); \( y_{\text{production and manufacturing}} = 1.570\% \); \( y_{\text{medicine}} = 1.538\% \); \( y_{\text{engineering and science}} = 1.525\% \).) Although medicine might seem as an outlier given the challenge topics, it could be argued that usage of instrument and machinery for problem solving is a common professional requirement for the medical professionals. Therefore, a challenge seeking complex engineering designs and solutions, such as ACS, might attract medical professionals.

Other non-STEM fields such as arts, law, and education exhibit lower yield than the average population. Although a STEM background generally relates to a higher yield, interestingly, people with IT background have a lower yield of quality solutions than average (\( y_{\text{IT}} = 0.568\% \)). We suspect the
majority of hardware-based problems in the ACS sets a specific knowledge threshold for contributing quality engineering designs. See Figure 4.9 for the comparison on the number of individuals within each career field (left y-axis) and the yield of quality solution (right y-axis.) Notice the STEM backgrounds have higher yields in general, except in IT. Medicine is an outlier in the non-STEM field with relatively high yield.

Figure 4.9 Comparison on Yield Across Career Field for ACS Crowd

We apply one-way ANOVA and Tukey HSD test to check whether the observed differences between STEM and non-STEM background are statistically significant. In this case, the dependent variable is the likelihood of generating quality solution while the independent variable is a dummy variable on whether someone has a STEM background or not. The results in Table 4.16 suggest that having a STEM background indeed introduces a significant difference by increasing the likelihood by 0.08%. In other words, if someone has a STEM degree, the person is statistically more likely to deliver a quality solution than those without.

This result makes sense as ACS poses a series of complex engineering problems, which might have entry barriers that requires some level of technical understanding. However, it does not support the assumption that reaching career field diversity, in this case, more non-STEM backgrounds, will lead to quality solutions.
Table 4.16 One-way ANOVA and Tukey HSD Results for Main Differences Between Having a STEM Background or Not

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

<table>
<thead>
<tr>
<th></th>
<th>d.f.</th>
<th>Sum of Squares</th>
<th>Mean Squares</th>
<th>F value</th>
<th>Pr (&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Having a STEM Background or Not</td>
<td>1</td>
<td>0.09</td>
<td>0.0860</td>
<td>9.413</td>
<td>0.0022 **</td>
</tr>
<tr>
<td>Residuals</td>
<td>9213</td>
<td>84.13</td>
<td>0.0091</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Tukey Multiple Comparisons of Mean

95% family-wise confidence level

<table>
<thead>
<tr>
<th>Mean Differences Across Having a STEM Background</th>
<th>Difference</th>
<th>Lower bound</th>
<th>Upper bound</th>
<th>P adjusted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes – No</td>
<td>0.0084</td>
<td>0.0030</td>
<td>0.0138</td>
<td>0.0022</td>
</tr>
</tbody>
</table>

4.2.1.6 Country Diversity and Solution Quality

ACS attracted a large group of people from underrepresented robotics regions to show up and submit quality solutions. While India was the most popular countries with most ACS registrants (2163 registrants), it has a relatively low likelihood of generating quality solution compared to the population baseline. Only 22 registrants proceeded in generating solutions. \( (\gamma_{\text{India}} = 1.02\%, \gamma_{\text{population}} = 1.16\%) \)

The US attracted second most participants to the challenge. However, it also has a lower than average quality solution probability \( (\gamma_{\text{US}} = 0.68\%, \text{with only 6 out of 887 registrants submit quality solutions.}) \)

While there is only one registrant reported from Sudan, that registrant proceeded in providing a quality solution, resulting a 100% yield, which highlights the inaccuracy of only looking at the yield. More analysis needs to be conducted in order to understand whether there exists statistical difference between countries and regions in this topic.

4.2.1.7 Motivation Diversity and Solution Quality

As discussed earlier, the ACS attracts a diverse set of motivation among its participants. Among the 6 types of motivations identified, the popularity of motivations follows as: Competent
(3473), Enthusiasts (3084), NASA Enthusiasts (1375), Problem Solver (995), Self-starter (632) and Extrinsic (302). However, the results on which motivation category yields more quality solutions are rather surprising.

While Self-starter and Extrinsic were the two least popular motivations among the ACS registrants, they turn out to be the two most productive motivations in generating quality solutions ($y_{\text{Self-starter}} = 2.057\%$, $y_{\text{Extrinsic}} = 1.673\%$). While a large proportion of ACS registrants indicate strong interests in the broadcasted problems or relevant SETM problems (“Enthusiast”), only a small fraction of these people ends up submitting any quality solution to the challenges, with the lowest yield among all motivational types ($y_{\text{Enthusiast}} = 1.102\%$). See Figure 4.10 for the comparison on the popularity of each motivational category (left y-axis) and the yields of solution quality (right y-axis).

This finding contribute to the earlier study of Maier (1946,) who suggested a functional relationship between individual’s performance with their ability and motivation as: Performance = f (motivation X Ability) [128]. Our data concludes that the least common motivations, Self-starter and Extrinsic, are the most productive in terms of leading to quality solutions. However, future analysis is needed to determine how motivation plays as a moderating variable in producing quality solutions in open innovation challenges.
4.2.2 Who are generating the quality solutions?

While the yield is one way of understanding where the quality solutions tend to arise, it has its own limitations. Yield can only signal quality solution in each diversity feature separately. Combining all the attributes with the highest yields together, there is likely a problem: someone who is a union of all attributes does not exist. In other words, who is more likely to contribute quality solutions is not the same as where the quality solution tends to arise.

Identifying a modal individual requires permuting multiple demographics attributes and ranking such combination by magnitude in order to identify the most represented demographic combination. We experiment with different representative attributes and levels of granularity within each attribute to select the representative group. We start with simple combinations of binary options and then add in more complicated attributes, such as: whether someone is male or female, whether someone is below or above 35 years old, what is someone’s highest education degree, and which region is someone from. Grouping the populations by these categories and rank the combinations by order, we learn the most common combination of these attributes among the ACS registrants. The modal ACS registrant is a male from Asia, who is aged below 35 and has the highest degree of the bachelors. There are 1760 individuals out of 9213 ACS registrants fit into this category, accounting for 19.1% of the population. From here, we add more attributes such as someone’s years of technical experience and their country of origin. This gives us a more detailed profile of the modal ACS registrant: someone who is a male, aged between 18-24, with a highest educational background of bachelor’s degree, from India, and with zero to five years of technical background. There are 531 individuals fitting into these descriptions, making up 5.7% of the ACS registrant population. See Table 4.17 for the top 10 modal ACS registrants.

In search for a representative ACS model quality solution submitter, we modify and adopt the categories of gender, age above or below 35 years old, with or without a Bachelor’s degree, and region of residency. The resulting modal submitter is someone who is a male, aged below 35 years old, with a Bachelor’s degree and from Asia. There are 18 submitters under this description, accounting for 21.2% of the population. Table 4.18 presents the top 10 modal ACS submitters results.

Both modal ACS registrants and modal submitters identified earlier are quite different from the model internal solver at NASA in terms of age, gender and work experience. The Modal internal solver is someone who ages between 50 – 54 years old, a male, with 25-29 years of serving experience. As derived from the WICN dataset, there are 582 individuals fitting these descriptions, accounting for = 3.55% in a total population of 16,410. The drastic differences on the age and experience between the two
modal profiles are a proof that ACS has indeed reached individual diversity compared to the internal workforce.

In addition, the findings on modal submitters confirms that who is more likely to contribute quality solutions is not the same as where the quality solution tends to come from. As Table 4.18 and Table 4.19 collectively show, a combination of the most productive subcategories within each attribute does not “sum up” to the same modal submitters identified in this section. This provides an important policy insight: focusing the most productive subcategories within each diversity feature, as what we did in the earlier sections of 4.3.1, is not enough to inform policy on where to seek quality solutions. It is important to be aware that the productive yields in each diversity feature only reveal a partial story of where quality solution tend to arise, and the study on individual diversity completes the rest of the story.

Table 4.17 Top 10 modal ACS registrants

<table>
<thead>
<tr>
<th>Gender</th>
<th>Age Group</th>
<th>Highest Education Degree</th>
<th>Country of Residency</th>
<th>Years of Technical Experience</th>
<th>Number of ACS Registrants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>18-24</td>
<td>Bachelor's</td>
<td>India</td>
<td>0-5</td>
<td>531</td>
</tr>
<tr>
<td>Male</td>
<td>18-24</td>
<td>High School</td>
<td>India</td>
<td>0-5</td>
<td>320</td>
</tr>
<tr>
<td>Male</td>
<td>25-34</td>
<td>Bachelor's</td>
<td>India</td>
<td>0-5</td>
<td>298</td>
</tr>
<tr>
<td>Male</td>
<td>25-34</td>
<td>Master's</td>
<td>India</td>
<td>0-5</td>
<td>124</td>
</tr>
<tr>
<td>Male</td>
<td>18-24</td>
<td>Bachelor's</td>
<td>Pakistan</td>
<td>0-5</td>
<td>121</td>
</tr>
<tr>
<td>Male</td>
<td>25-34</td>
<td>Bachelor's</td>
<td>India</td>
<td>5-10</td>
<td>86</td>
</tr>
<tr>
<td>Male</td>
<td>18-24</td>
<td>High School</td>
<td>United States</td>
<td>0-5</td>
<td>82</td>
</tr>
<tr>
<td>Male</td>
<td>18-24</td>
<td>High School</td>
<td>Pakistan</td>
<td>0-5</td>
<td>77</td>
</tr>
<tr>
<td>Male</td>
<td>18-24</td>
<td>High School</td>
<td>Bangladesh</td>
<td>0-5</td>
<td>73</td>
</tr>
<tr>
<td>Male</td>
<td>25-34</td>
<td>Bachelor's</td>
<td>United States</td>
<td>0-5</td>
<td>69</td>
</tr>
</tbody>
</table>
Table 4.18 Top 10 modal ACS Quality Solution Submitters

<table>
<thead>
<tr>
<th>Gender</th>
<th>Age Range</th>
<th>Education Level</th>
<th>Region</th>
<th>Number of ACS Submitters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>&lt;35</td>
<td>With Bachelor's</td>
<td>Asia</td>
<td>18</td>
</tr>
<tr>
<td>Male</td>
<td>&lt;35</td>
<td>With Bachelor's</td>
<td>Americas</td>
<td>9</td>
</tr>
<tr>
<td>Male</td>
<td>&gt;35</td>
<td>With Bachelor's</td>
<td>Americas</td>
<td>8</td>
</tr>
<tr>
<td>Male</td>
<td>&lt;35</td>
<td>With Bachelor's</td>
<td>Europe</td>
<td>8</td>
</tr>
<tr>
<td>Male</td>
<td>&gt;35</td>
<td>With Bachelor's</td>
<td>Asia</td>
<td>7</td>
</tr>
<tr>
<td>Male</td>
<td>&lt;35</td>
<td>Without</td>
<td>Americas</td>
<td>5</td>
</tr>
<tr>
<td>Male</td>
<td>&gt;35</td>
<td>With Bachelor's</td>
<td>Europe</td>
<td>3</td>
</tr>
<tr>
<td>Male</td>
<td>&gt;35</td>
<td>Without</td>
<td>Americas</td>
<td>3</td>
</tr>
<tr>
<td>Male</td>
<td>&lt;35</td>
<td>With Bachelor's</td>
<td>Africa</td>
<td>3</td>
</tr>
<tr>
<td>Male</td>
<td>&lt;35</td>
<td>Without</td>
<td>Europe</td>
<td>3</td>
</tr>
</tbody>
</table>

Table 4.19 Most productive subcategory with highest yield of quality solutions

<table>
<thead>
<tr>
<th>Diversity Feature</th>
<th>Highest Yield Subcategory</th>
<th>Yield</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>Male</td>
<td>0.97%</td>
</tr>
<tr>
<td>Age</td>
<td>35-44</td>
<td>1.50%</td>
</tr>
<tr>
<td>Years of Experience</td>
<td>15 - 19 years</td>
<td>2.20%</td>
</tr>
<tr>
<td>Highest Education Level</td>
<td>Master's degree</td>
<td>1.256%</td>
</tr>
<tr>
<td>Country</td>
<td>Sudan</td>
<td>100%</td>
</tr>
</tbody>
</table>

4.2.3 Key Takeaways for RQ2: To what extent has diversity been reflected in obtaining quality solution?

In section 4.2, I addressed the second research question of this thesis: to what extent has diversity been reflected in obtaining quality solutions? Insights from the study show that diversity in certain features does not necessarily lead to quality solutions. Based on descriptive statistics, we observe nuances in terms of which subcategory within diversity features tend to generate more quality solutions. For example, aging between 35-44, having 15-19 years of technical experience, and having a master’s degree are more likely to generate quality solution. We also further test the statistical significance of some diversity features and link the findings back to the literature. We found that
Generation Y, having a bachelor’s degree, and having a STEM background explains quality solution significantly from a statistical sense. The divergent findings on where and from whom do quality solutions come from provide further insights in understanding the relationship between diversity and productive innovation.

With the results represented, I will then transition to the policy implications based on these results in the next chapter.
Chapter 5 Policy Implications and Conclusion

Knowing the extent to which the crowd is diverse and where quality solutions tend to come from, what does it mean for federal agencies to leverage open innovation challenges in the future? In this chapter, I present the summary of results in section 5.1 and policy implications for STEM-focused public agencies in section 5.2. I conclude with future work and closing remarks in section 5.3.

5.1 Summary of Results

Achieving diversity in STEM fields is an urgent and important task faced by many US federal agencies [27], [35], [40], [45]. Despite previous efforts, agencies are still actively exploring methods and tools that will enable them to increase diversity, particularly in fields of STEM. In the past decade, open innovation challenges have become popular within the government [2], [8]. Rising with its popularity is the hope that such innovation mechanism would reduce barriers to participate in STEM fields, therefore increasing diversity for agencies. Due to a lack of data about the participation in open innovation challenges, there has been limited analysis done to address this potential directly.

To that end, this thesis addresses two research questions, hoping to shed some light on this important societal topic. In particular, it asks:

1. Given the policy objective of increasing diversity in STEM fields, to what extent have federal open innovation challenges reached a more diverse population of solvers?
2. To what extent, if at all, has achieving increased diversity led to innovative solutions?

This thesis utilizes the NASA-Freelancer Astrobee Challenge Series (ACS), a robotics design prize challenge, as a case study. This unique field experiment offers a fitting context to study a crowd of 9000+ who participated in a STEM space robotics challenge.

Regarding the first research question, our results show that open innovation challenges like the ACS do not achieve all types of diversity, in terms of diversity dimension or feature, all the time. In relation to previous expectations on the diversity performance of prize challenges, as embedded in policy discussions and literature, our findings conflict with some of them but support most of the others.
For example, many agencies have a diversity goal in increasing female representation in their workforce [27][37][38][40][43], and hope that an open innovation challenge to be an effective tool for such cause. This is because such challenges are likely to “pose problems and opportunities to all available pools of talent [114],” and in that process, encouraging more women to participate in the traditionally male-dominated STEM fields. However, our findings reveal that ACS is not that effective in attracting more females into solving STEM problems, as there is an even more drastic female underrepresentation in the ACS crowd when compared to that of the NASA internal solvers.

On the other hand, our results support that ACS is effective in attracting a younger and more even age profile in the crowd than the internal solvers who are tasked the same problems. Our data also reveal a population with less work experience, fitting into the definition of “young professionals.” Reaching a younger population as such is one of the many diversity goals identified by federal agencies, particularly when some of them are facing an age “cliff” in their own workforce [117], [118]. Compared to the internal solvers, the ACS crowd also have relatively lower education attainment levels, which differentiate them further from the internal workforce in many STEM-focused federal agencies. In response to the debate on whether a prize challenge would benefit from a global or domestic participation [22],[166], ACS shows that if an open innovation challenge is broadcast outside of the US, there is a large, interested and capable crowd ready to solve the problem. Many of them are from unexpected locations for soliciting robotics solutions. The crowd also present a more diverse set of work experience than the internal solvers at the sponsoring agency, as their backgrounds are not strictly tied to STEM fields, despite their task is a complex engineering problem. Through our unique approach of pairing inductive coding and natural language processing, our findings uncover a diverse set of motivations among the crowd.

Even though the ACS fails to achieve diversity goals in some respect, such as in gender, it still achieves a more diverse population than the internal solvers in other attributes such as age, country, work experience, and education level. Specifically, the ACS crowd is more diverse because they are: younger, representing more countries, with more and different work experience (including non-STEM expertise,) and having different education attainment levels, when compared to the internal solvers.

In response to the second research question, it is found that the more diverse solvers identified in ACS are not equally responsible for generating productive innovation.

In particular, while it is part of agencies’ diversity goals to reach a younger population [22],[37], and indeed ACS achieves that goal, not all young crowds are equally likely to generate quality solutions. Among the younger population, only Generation Y has a higher probability of generating productive
innovation. Similarly, it is part of the departmental diversity goals to reach a population of different educational backgrounds, and ACS serves that goal. From our data, people with a bachelor’s degree and above are more likely to generate quality solution. While there are more people with lower education attainment when compared to the internal solvers, it is inconclusive from our data to judge whether the less educated population (with only bachelor’s degrees or below) are more likely to generate quality solution or not. Future work is needed to clarify this topic. ACS also reaches a diverse crowd from 147 countries, fulfilling many agencies’ open innovation strategies of a reaching a global solver base [23], [114], [115]. Among the ACS solvers, foreign (non-U.S.) participants have a higher probability of generating quality solutions than the U.S. contestants, suggesting that a foreign crowd does lead to quality innovation in a prize challenge.

On the other hand, even though ACS reaches a population with non-STEM backgrounds, which satisfies some agencies’ diversity goals [40], [24], this population is less likely to generate productive solutions, perhaps due to the technical barriers posed by the problems. Similarly, people with less than 10 years of experience might also be hindered by a lack of prior and relevant knowledge in this particular challenge, despite they fulfills the diversity goal on young professionals. See Figure 5.1 for a visualization of the discussion above.

Figure 5.1 Summary of results to RQ2

<table>
<thead>
<tr>
<th>Productive Innovation</th>
<th>Unproductive Innovation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation Y (Age 25-44)</td>
<td>Females</td>
</tr>
<tr>
<td>Foreign Countries (expected and unexpected)</td>
<td>Generation Z (18-24)</td>
</tr>
<tr>
<td>People with 15-19 years of work experience</td>
<td>People with &lt;10 years of work experience</td>
</tr>
<tr>
<td>People with a Bachelor’s degrees and above</td>
<td>People with non-STEM background</td>
</tr>
</tbody>
</table>
5.2 Policy Implications

In this section, we discuss how the diversity objectives, whether an internal departmental diversity goal or expected diversity outcomes of open innovation, have been served by a prize challenge like the ACS. Based on the discussion, we also provide a series of policy implications.

Before delving into the mapping of results to stated diversity goals, one initial policy observation is the overlap between some of the diversity goals in agencies’ departmental plans and open innovation strategies. The departmental diversity plan and open innovation strategy are fundamentally serving two purposes for a federal agency, with the prior focusing on the workforce while the latter primarily on generating innovation. Recognizing where the two sets of diversity objectives overlap is an important step to understand the rationale and limitation of using open innovation as a potential policy mechanism for diversity. Table 5.1 provides the comparison.

<table>
<thead>
<tr>
<th>Selected STEM Federal Agencies</th>
<th>Departmental Diversity Goals</th>
<th>Open Innovation Strategy on Supporting Diversity</th>
<th>Can open innovation strategy serve the departmental diversity objective?</th>
</tr>
</thead>
<tbody>
<tr>
<td>NASA</td>
<td>NASA needs to be reflective of the diversity of America at all levels of the organization. [35]</td>
<td>[…] readily increases its creative capacity and reach by tapping into diverse talent from around the world [23]</td>
<td>Partially.</td>
</tr>
<tr>
<td></td>
<td>[...] Individuals from a wide variety of backgrounds, skills, and abilities that can bring unique perspectives, and life experiences, to tackle highly complex challenges to achieve NASA's mission. [38]</td>
<td>[...] harnessing the perspectives, expertise, and enthusiasm of “the crowd” outside their walls to reduce costs, accelerate projects, enhance creativity, and better engage their stakeholders [112].</td>
<td>Open innovation strategies (right) serve the departmental objective (left) in seeking deep-level diversity features such as backgrounds, skills, perspectives and expertise.</td>
</tr>
<tr>
<td></td>
<td>NASA’s Special Emphasis Programs (SEP) focus on nine critical segments of our workforce: African American; American Indian/Alaska Native; Asian American/Pacific Islander; Hispanic/Latino; Individuals with Disabilities; Lesbian, Gay, Bisexual, Transgender &amp; Allies; Veterans; Women; Young Professionals. [37] [38]</td>
<td>No specific demographic/ethnic groups mentioned</td>
<td>When it comes to who to reach and why to reach them, the departmental goal focuses on the American population and for their demographics, whereas the open innovation strategy has a broader focus on global population and for their talents.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Also, NASA’s open innovation strategy does not target at specific groups as the departmental goals do.</td>
</tr>
</tbody>
</table>
Table 5.2 (Continued) Overlaps Between Departmental Diversity Goal and Open Innovation Strategy

<table>
<thead>
<tr>
<th>Selected STEM Federal Agencies</th>
<th>Departmental Diversity Goals</th>
<th>Open Innovation Strategy on Supporting Diversity</th>
<th>Can open innovation strategy serve the departmental diversity objective?</th>
</tr>
</thead>
<tbody>
<tr>
<td>NSF</td>
<td>NSF’s goal in workforce diversity is to recruit from a diverse, well qualified group of potential applicants to secure a high-performing workforce <strong>drawn from all segments of American Society</strong>[40]</td>
<td>Positive near-term impact of Innovation Inducement Prizes at the National Science Foundation: Whether the contests attract large numbers of contestants.</td>
<td>Partially. Both goals are centered around US population. The NSF open innovation strategy (right) is slightly broader by including U.S.-registered subsidiaries of foreign-based companies and temporary immigrants on study or work visas [22]. However, while the departmental goals (left) define diversity with a more extensive list of features, the open innovation strategy does not contain such list and only specify “students and young professionals.” While the departmental goals specifically seek racial/ethnic minority groups and persons with disability, the open innovation strategy seeks a rather broad audience that are “a more diverse group than the traditional NSF constituency [22].”</td>
</tr>
<tr>
<td>NIST</td>
<td>NIST continually strives to establish and maintain a <strong>workforce that reflects America's diverse populace</strong> and promotes an environment that respects and values individual differences[45]. NIST recognizes that the ability to recruit, develop, and retain a <strong>highly skilled and diverse workforce</strong> is key to the Institute’s continued success [45].</td>
<td>We are to implement prize challenges <strong>in order to reach solvers from around the world to help us reach our goals</strong> [115]. NIST and the challenge partners understood that the experts who could produce better materials could be found in a <strong>hugely diverse set of communities, from aerospace to automotive to sports medicine</strong>[115].</td>
<td>Partially. Both strategies recognize the importance of a diverse community and seek deep-level diversity attributes such as skillsets and field of expertise. In addition, NIST’s departmental goals (left) focus on a diverse American population while its open innovation goals seek a broader global representation.</td>
</tr>
</tbody>
</table>
Table 5.2 (Continued) Overlaps Between Departmental Diversity Goal and Open Innovation Strategies

<table>
<thead>
<tr>
<th>Selected STEM Federal Agencies</th>
<th>Departmental Diversity Goals</th>
<th>Open Innovation Strategy on Supporting Diversity</th>
<th>Can open innovation strategy serve the departmental diversity objective?</th>
</tr>
</thead>
<tbody>
<tr>
<td>DOE</td>
<td>At DOE, as a science and technology agency, we have unique diversity characteristics that must be addressed. This includes the broad spectrum of characteristics including, but not limited to, race, color, ethnicity, national origin, gender, age, religion, culture, language, disability, sexual orientation, gender identity, socioeconomic status, family structures, geographic differences, diversity of thought, technical expertise, and life experiences [27].</td>
<td>Prizes may be appropriate for use when: … expand a program’s reach to citizen solvers and entrepreneurs of diverse backgrounds, skill sets, and experience [24]. […] Bring out-of-discipline perspectives to bear [24].</td>
<td>Partially. While DOE’s goal addresses a range of features, the open innovation strategy only mentions a subset of deep-level diversity features, such as backgrounds, skill sets, and experience. The departmental internal goals seek a diverse US domestic population while open innovation goals do not specify a particular group.</td>
</tr>
<tr>
<td>HHS</td>
<td>We define diversity as all the ways in which people differ, including innate characteristics (such as age, race, gender, national origin, mental or physical abilities and sexual orientation) and acquired characteristics (such as education, socioeconomic status, religion, work experience, language skills, cultural values, geographic location, family status, organizational level, work style, philosophical and intellectual perspectives, etc) [42]. […] Special Emphasis Programs (at HHS) are management programs established to ensure equal employment opportunity for minorities, women, veterans and persons with disabilities in various categories and occupations, and in all organizational components throughout the Department [43].</td>
<td>Specifically, we provide value by: […] posing problems and opportunities to all available pools of talent, increasing the number of people, organizations and companies working on a problem and stimulating markets to develop a robust eco-system of approaches [114].</td>
<td>Partially While HHS’s departmental goals are quite specific in features that define diversity, the open innovation strategy is rather broad. Also, there isn’t specific racial/ethnic or demographic group identified in the open innovation statements.</td>
</tr>
</tbody>
</table>

After reviewing the comparison between agencies’ departmental goals and open innovation strategies focusing on diversity, we come to our first policy implication.
Policy Implication #1: Open innovation strategies may serve some departmental diversity goals

As shown in the second column of Table 5.1, there are several common themes among agencies’ departmental diversity goals: 1) many agencies seek a workforce that reflects America’s diverse population (ie. NASA, NSF, DOE, and NIST); 2) they define diversity by a broad range of characteristics, including surface diversity attributes like race, color, ethnicity, national origin, gender, age, and deep-level attributes like education, socioeconomic status, skills, perspectives, and so on (ie. NASA, NSF, DOE, HHS); 3) some agencies identify specific groups for special attention, such as racial/ethnic minorities, women, veterans and persons with disabilities (ie. NASA, NSF, and HHS). These themes all roughly point to one direction: agencies look for a diverse population and their represented demographics.

Similarly, open innovation strategies (third column) also look for a diverse population. In the cases of NASA, NSF and NIST, they seek a diverse employee base that reflects the demographic diversity of the American population. At the same time, they also actively seek a diverse crowd from all around the world, hoping to “reach solvers from around the world to help them reach their goals”[115]. While the scope of populace is different in both diversity goals, the pursuit for a diverse population is shared.

While the departmental goals tend to seek a diverse population for their demographics, open innovation strategies seek a diverse population for their talents. When it comes to deep-level diversity attributes such as “perspectives, expertise”[112], “backgrounds, skill sets, and experience”[24], there are large overlaps between agencies’ departmental diversity goals and open innovation strategies. As exemplified by the cases of NIST, DOE, and NASA, these deep-level diversity attributes are important to agencies’ departmental diversity goals, as well as to the success of open innovation initiatives.

However, despite the overlaps identified above, there are areas where the two polices diverge. Many federal agencies (like NASA, NSF, and HHS) have departmental diversity goals specifically targeting underrepresented racial/ethnic groups, persons with disabilities, veterans, and other minorities. These internal diversity goals for specific demographic or racial/ethnic groups are not served by agencies’ open innovation strategies, as they are rarely mentioned in the latter.

The overlaps between the two sets of diversity goals indicate that open innovation strategies, when achieved, will serve some of agencies’ departmental diversity goals.
Is a prize challenge like the ACS an effective in serving departmental diversity goals?

Regarding how a prize challenge like the ACS helps serve these stated diversity goals by agencies, particularly where the goals overlap, we refer to Table 5.2 for a mapping of these objectives to the analysis results.

Table 5.2 Summary on Diversity Policy Goal in Comparison to Results of ACS

<table>
<thead>
<tr>
<th>Selected STEM Federal Agencies</th>
<th>Departmental Diversity Goals</th>
<th>Open Innovation Strategy on Supporting Diversity</th>
<th>How does a prize challenge like the ACS serve these diversity goals?</th>
</tr>
</thead>
<tbody>
<tr>
<td>NASA</td>
<td>[...] Individuals from a wide variety of backgrounds, skills, and abilities that can bring unique perspectives, and life experiences, to tackle highly complex challenges to achieve NASA’s mission. [38]</td>
<td>[...] harnessing the perspectives, expertise, and enthusiasm of “the crowd” outside their walls to reduce costs, accelerate projects, enhance creativity, and better engage their stakeholders [112].</td>
<td>The ACS serves the goals in deep-level features such as education level, work experience, years of experience, and reaching more young professionals.</td>
</tr>
<tr>
<td></td>
<td>NASA’s Special Emphasis Programs (SEP) focus on nine critical segments of our workforce: ... Young Professionals. [37] [38]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NSF</td>
<td>NSF’s goal in workforce diversity is to recruit from a diverse, well qualified group of potential applicants to secure a high-performing workforce drawn from all segments of American Society[40]</td>
<td>Positive near-term impact of Innovation Inducement Prizes at the National Science Foundation: Whether the contests attract large numbers of contestants [...] whether those contestants are a more diverse group than the traditional NSF constituency [22].</td>
<td>The ACS serves diversity in multiple attributes such as educational background, age, years of work experience, and national origin that are also different than the traditional NSF constituency. It also attracts more young professionals and students, despite that is more relevant to the open innovation strategy.</td>
</tr>
<tr>
<td></td>
<td>These include, but are not limited to, characteristics such as national origin, [...]age[...]educational background. The concept also encompasses differences among people concerning where they are from and where they have lived and their differences of thought and life experiences [40.]</td>
<td>Attracting diverse participants in the competition, involving students and young professionals [...] [22].</td>
<td>Given the 9000+ crowd attracted, the ACS is indeed reaching “large numbers of contestants[22].” There are 887 contestants “drawn from the American Society [40]”, therefore also serving the departmental goals.</td>
</tr>
</tbody>
</table>
Table 5.3 (Continued) Summary on Diversity Policy Goal in Comparison to Results of ACS

<table>
<thead>
<tr>
<th>Selected STEM Federal Agencies</th>
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<th>How does a prize challenge like the ACS serve these diversity goals?</th>
</tr>
</thead>
<tbody>
<tr>
<td>NIST</td>
<td>NIST continually strives to establish and maintain a workforce that reflects America’s diverse populace and promotes an environment that respects and values individual differences[45]. NIST recognizes that the ability to recruit, develop, and retain a highly skilled and diverse workforce is key to the Institute’s continued success [45].</td>
<td>We are to implement prize challenges in order to reach solvers from around the world to help us reach our goals [115]. NIST and the challenge partners understood that the experts who could produce better materials could be found in a hugely diverse set of communities, from aerospace to automotive to sports medicine[115].</td>
<td>The ACS crowd come from around the world, with 887 contestants from the U.S, therefore serving the departmental goals. The ACS also represent a wide range of fields and skills that matter for the agency, such as in work experience and education experience.</td>
</tr>
<tr>
<td>DOE</td>
<td>At DOE, as a science and technology agency, we have unique diversity characteristics that must be addressed. This includes the broad spectrum of characteristics including, but not limited to, […]national origin, […] age, […]geographic differences, diversity of thought, technical expertise, and life experiences [27].</td>
<td>Prizes may be appropriate for use when: … expand a program’s reach to citizen solvers and entrepreneurs of diverse backgrounds, skill sets, and experience[24]. […]Bring out-of-discipline perspectives to bear[24].</td>
<td>ACS reaches diversity in national origin, age, geographic differences, technical expertise, life experience (if measured by work experience), diversity of thoughts (as a result of all the above features), and solvers with non-STEM background as “out-of-discipline perspectives. [24]”</td>
</tr>
<tr>
<td>HHS</td>
<td>We define diversity as all the ways in which people differ, including innate characteristics (such as age, […], national origin […]and acquired characteristics (such as education, […], work experience, […]geographic location, […]philosophical and intellectual perspectives, etc)[42].</td>
<td>Specifically, we provide value by: […] posing problems and opportunities to all available pools of talent, increasing the number of people, organizations and companies working on a problem and stimulating markets to develop a robust eco-system of approaches [114]</td>
<td>The ACS serves diversity goals in age, national origin, education, work expertise, geographic location. It also “increases the number of people” who would work on a problem as it reached a crowd outside of the agency, meeting both departmental and open innovation goals. However, it is hard to judge whether it reaches “all available pools of talent”.</td>
</tr>
</tbody>
</table>

**An Agency-by-agency Review**

**NASA:** NASA recognizes the importance of workforce diversity and aims to reflect the “diversity of America” in its stated departmental diversity goals [35]. It also supports diversity through open innovation initiatives because they allow “tapping into diverse talents from around the world”
The ACS result verifies the expected open innovation outcome by attracting a large number of solvers, mostly from outside of the U.S. Even though the crowd is not a strict representative of the U.S. population, the ACS helps reach a diverse population.

NASA also further defines diversity based on a set of deep-level attributes such as “background, skills, and abilities” [38] in its internal diversity statement. These deep-level diversity goals are served quite well by a prize challenge like the ACS, as shown in the results on education level, work experience, and years of experience.

However, NASA’s internal diversity objectives also identify a series of absolute diversity goals, whose representations NASA hopes to increase inside its organization [37]. These are the groups in the Special Emphasis Programs (SEP) [38]. On this front, a prize challenge like ACS clearly fails on the diversity of females, even though it achieves the diversity of young professionals. As for the other diversity targets on racial/ethnic representation, persons with disabilities, sexual orientation, and veteran’s status, unfortunately, the current ACS data does not contain such information. In order to assess these features as parts of the expressed goals, future data collection on prize challenge participation should expand and include these attributes.

In all, an open innovation challenge like the ACS is effective to serve NASA’s internal diversity goals of reaching young professionals, a wide variety of education levels, work experience, and years of experience. It is not so helpful in introducing more women into STEM fields.

**NSF:** As a federal agency, NSF also expects its internal workforce to be “drawn from all segments of American society” [40]. When it comes to open innovation diversity goals, the near-term positive targets are defined as “whether it allows reaching a number of contestants”, and “whether those contestants are a more diverse group than the traditional NSF constituency” [22]. The ACS is not a direct reflection of the American society, however, it does reach a large number of contestants, and representing a “more diverse group than the traditional NSF constituency” [22].

If judged by attributes of educational backgrounds, age, years of work experience and national origin, ACS indeed serve these goals by reaching a population that differ from the internal solvers; specially reflected through their education attainment, age profile, work experience and nations of residency. As identified in the NSF departmental objectives, these attributes “encompasses differences among people concerning where they are from and where they have lived and their differences of thought and life experiences”[40]. Due to the limitation on data, our results do not provide insights into whether racial/ethnic diversity has been achieved, which is one of many key diversity metrics presented in the NSF internal diversity statement.
In all, a prize challenge like the ACS is successful in a few attributes such as educational backgrounds, age, years of work experience and national origin. However, due to data limitation, it is not readily serving other diversity goals, such as racial/ethnic diversity, identified in the NSF departmental diversity objective.

**NIST:** Similar to the above cases, NIST also seeks to “establish and maintain a workforce that reflects America’s diverse populace” [45]. In elaborating its support for open innovation, it specially identifies the goal to “reach solvers from around the world” [115]. In this sense, a prize challenge like the ACS is partially serving the agencies’ goal given it is not a direct reflection the U.S. population but a diverse group.

In addition, the ACS crowd represents a wide range of fields and skills, as measured by their work and education experience, which supports both the internal diversity goals and open innovation strategy of NIST. The diverse work and educational backgrounds in the ACS lend support to the stated goal of: “(reaching) a hugely diverse set of communities, from aerospace to automotive to sports medicine” [115].

Therefore, an open innovation challenge like the ACS is helpful to achieve parts of NIST’s departmental diversity goals, particularly in reaching a variety of work and education backgrounds.

**DOE:** In DOE’s case, a prize challenge like the ACS serves a mix of the agency’s diversity objectives.

In terms of the presenting desirable diversity features in the DOE workforce, a prize challenge like the ACS is successful in national origin, age, geographic differences, technical expertise, life experience (if measured by work experience) and diversity of thoughts (as a result of all the above features.) However, it is not so effective in reaching the gender diversity goal. It does not contain information for the remaining targets, such as race, color, disability, ethnicity, religion and others. On the other hand, the ACS result reaffirms the diversity expectation detailed in DOE’s open innovation strategy, such as “bringing out-of-discipline perspectives to bear,” and “expanding a program’s reach to citizen solvers and entrepreneurs of diverse backgrounds, skill sets, and experience.”

**HHS:** Similar to the above case, ACS contributes partially to HHS’s departmental diversity goal, in attributes such as age, national origin, education, work expertise, and geographic location. However, due to data limitation, it fails to address other features of interest such as family statues, organizational level, work style. Regarding one of the key goals of HHS is to increase female representation, a prize challenge like the ACS is not an effective mechanism. HHS considers the value of open innovation in “posing problems and opportunities to all available pools of talent, increasing
the number of people, organizations and companies working on a problem” [114]. ACS indeed increases the number of people who would work on a problem as it reaches an external crowd outside of the agency. However, it is rather hard to judge whether that equalizes with “all available pools of talent.” In absence of a more specific goal on HHS open innovation initiatives, it is rather difficult to determine the extent to which diversity goal has been achieved.

_Policy Implication # 2: Prize Challenges serve multiple (but not all) departmental diversity goals_

After reviewing the results on agencies above, it is clear that a prize challenge like the ACS is effective in reaching multiple diversity goals identified in agencies’ departmental diversity goals.

In particular, it serves their objectives in reaching a large number of people [40], many of whom are young professionals and students [22],[37], [38]. It also serves to reach a variety of deep-level attributes, such as educational backgrounds, work experience, and years of experience. It attracts a population with different skill sets, expertise, and perspectives, which are desirable to many of the federal agencies [27],[38],[40],[42]. Lastly, the ACS is effective in tapping into talents from the world, representing one of the diversity goals in national origin [27],[42]. However, it is also found that a prize challenge like the ACS fails to solve a rather fundamental diversity target, which is the lack of female representation in STEM fields. In addition, it is yet to be determine that whether an open innovation challenge solves some other key diversity objectives such as racial/ethnic representation, people with disabilities, veterans, and so on, given thier frequent mentions in federal agencies’ departmental statements.

In the above areas where a prize challenge does serve diversity goals, future organizations should exploit this mechanism further to receive its benefits in advancing diversity. However, it is also shown that a prize challenge is not effective in achieving all aspects of diversity. In areas like these, other open innovation tools or policy mechanism should be in place. A clear identification of departmental diversity needs by future organizations is important for evaluating and determining whether a prize challenge is the most appropriate tool serve those needs.
Policy Implication #3: Generation Y, Foreign (non-U.S.) Contestants and People with a Bachelor's Degree could be target groups for federal prize challenge on complex engineering problems

The ACS is a NASA-sponsored open innovation challenge series, where it broadcasts a total of 17 complex robotics design problems to an external crowd, with topics ranging from autonomous deployment and positioning system design to software architecture design.

Earlier discussions show how the mechanism of an open innovation challenge help agencies reach some of its desired diversity outcomes, such as a younger population, a variety of education and expertise, a large number of national origin representation, and so on. However, it is also found that among these more diverse groups, only a few are responsibly for generating quality innovation in an open innovation challenge that focuses on complex engineering problems.

Generation Y among the younger population, foreign (non-U.S.) contestants, and people with a Bachelor’s Degree and above are statistically more likely to generate quality solutions compared to other age groups, the U.S contestants and education degrees. In other diversity attributes such as gender and years of experience, our results are not statistically significant to explain whether certain gender group or certain range of experience is more responsible for quality solutions or not.

For future open innovation challenges operating in a similar problem domain, that is, complex engineering problems, the three identified groups above might serve as the targeting audience to increase both the solution quality and diversity performance of these competitions.

Policy Implication #4: A need for specified diversity objectives for agencies

As discussed earlier, current departmental diversity goals and open innovation strategies remain rather inconsistent within and across agencies.

In their departmental diversity plans, some agencies define diversity rather broadly (ie. “diversity is the similarities and differences in the individual and organizational characteristics that shape our workplace [35]), while others provide a list of characteristics without justifications [27],[40]. The issue with such vague definitions is that they lead to an ambiguous interpretation on how to reach, measure, and enhance the diversity targets. Furthermore, the current statements do not provide guidance on how to quantify each attribute – whether measured by its quantity, proportion or comparison to other criteria.
Similarly, some of the open innovation strategies define diversity goals rather loosely (i.e. “(open innovation) provide value by posing problems and opportunities to all available pools of talent [114]”). These unclear definitions and objectives pose a challenge to accurately benchmark the diversity performance of open innovation initiatives to the stated goals.

Earlier policy implications show that a prize challenge like the ACS, as one of many forms of open innovation initiatives, is not an omnipotent tool in serving all stated diversity goals. In fact, it performs effectively in certain areas and within which, some attributes are more responsible in generating quality innovation than others. In order to make the best use of a prize challenge in the future, agencies should start with specifying its desired diversity needs in more details, and map those to the achievable areas of a prize challenge. In particular, it is suggested that agencies:

1) provide more systematic and consistent definitions on diversity, particularly within their agency;

2) identify diversity targets and choose the most appropriate measuring framework given agencies’ own context, i.e. whether a diversity attribute should be measured from a population perspective using scores of unalikeableness, or relative perspective by contrasting with another population, or absolute perspective by measuring the absolute number and proportion;

3) and lastly, update the open innovation strategies to reflect the departmental diversity goals more closely. With the insights generated by this thesis, agencies now have the knowledge on where a prize challenge could serve certain goals and where it could not. From there, agencies may exploit prize challenges and other open innovation tools more efficiently to further their goals.
5.3 Future Work and Conclusions

While this thesis has contributed to several key research gaps, it also generated open questions that will keep advancing our understanding of the crowd and the mechanism of open innovation challenges. Future work in this field could pursue the following:

Further understanding the ACS crowd

- Why is there an absence of females in open innovation challenges? Why is there a drop of female participation in submitting quality solution? While we learn about the female absence in this study, we still are left uncertain of the potential reasons and rationale behind this phenomenon. By contrasting the motivational differences between male and female participants, as well as those of female submitters and registrants, future study could gain additional information regarding this issue.

- Given the large presence of ACS participants coming from regions with developing robotics industries, it is natural to ask: what motivates them in participating an open innovation challenges like ACS? Why aren’t there more people from the developed robotics countries participating ACS? Future studies focusing on motivations from these different population could reveal additional insights on this topic.

Further understanding the mechanism of open innovation challenges

- Whether and how motivation plays as a moderating variable in producing quality solutions in open innovation challenges? By constructing a contingency table that relates motivation types and diversity features, future research may compare the composition of diversity feature in each motivation to answer why self-starter and extrinsic become the most productive motivation types for quality solutions in ACS.

- Why certain achieved diversity features lead to productive innovation but not others? While it is an important finding that Generation Y, solvers from foreign countries, and people with a bachelor’s degree and above are more likely to generate quality solutions in a prize challenge like the ACS, future work is needed to understand what makes these features stand out.
Further understanding the policy implications of open innovation challenges

- Due to the data limitation on features such as race, ethnicity, veteran’s status, and disabilities, this thesis is unable to measure and evaluate the effectiveness of an open innovation challenge like the ACS in achieving agencies’ departmental diversity goals in these regards. Future data collection could include additional diversity features as such. Given the sensitive nature of such data, the collection process might need to modified in order to pass relevant Institutional Review Board (IRB) approval, which serves to protect the rights and welfare of human subjects[174].

In conclusion, this thesis furthers the understanding on the extent to which an open innovation challenge is a useful tool for achieving high-level innovation and diversity goals for STEM federal agencies. For the most part, we find that an open innovation challenge like the ACS is not effective in reaching every stated diversity goal. Hence, it should not be considered as a one-stop shop policy mechanism to achieve all stated diversity objectives. A relevant policy discovery is that not all open innovation strategies can readily serve the departmental diversity goals of federal agencies. Therefore, it is important to specify the expected outcomes of future open innovation challenges accordingly, including focusing on where diversity goals are achievable and where diversity brings value to the origination. Additionally, our results show that not all achieved diversity goals lead to productive innovation. However, in areas where it does generate diversity and such diversity does translate into quality solutions, future challenge organizers should exploit this mechanism further.
# Appendix I

One-way ANOVA and Tukey HSD Results for 5-year-interval Age Group Main Difference

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

109 observations deleted due to missingness

## One-Way ANOVA Results

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<th>Generation Groups</th>
<th>d.f.</th>
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<th>F value</th>
<th>Pr (&gt;F)</th>
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## Tukey Multiple Comparisons of Mean

95% family-wise confidence level

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<th>Upper bound</th>
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