Investigating perceptions of intelligence as an approach to understanding female representation in technology and engineering education

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Abstract

Gender representation in technology and engineering education is generally not equitable with females being underrepresented in many areas (e.g. Sultan, Axell, & Hallström, 2018; Yoder, 2017). While there are many perspectives on gender representation in technical fields, from the perspective of advancing engineering and technology as disciplines, an underrepresentation of females indicates a potential loss of talent. It is therefore pertinent to continue trying to understand why this gender disparity exists.

The field-specific beliefs hypothesis (Leslie, Cimpian, Meyer, & Freeland, 2015) suggests that women are underrepresented to a greater extent in academic disciplines perceived by practitioners to require more raw intellectual talent. In a large scale study, Leslie et al. (2015) provided evidence supporting this hypothesis above three competing hypotheses. Based on these findings, this study explores what 'raw intellectual talent' is perceived to mean in engineering.

In a previous study, Buckley, O'Connor, Seery, Hyland and Canty (2018) found that undergraduate initial technology teacher education students in Ireland perceived intelligence in technology education to describe three components of general, social and technological competence. In this study, the methodology used by Buckley et al. (2018) will be adopted for the context of engineering. A survey asking what characteristics describe intelligence in engineering was administered to university students pursuing bachelor's and master's degrees in a variety of engineering fields in both Ireland and Sweden. The data was coded both inductively and deductively, and frequency statistics were used to analyse the data.

The results suggest that engineering likely has a unique characteristic in terms of engineering competency, and that is it probably knowledge based. In terms of future work regarding gender differences, this suggests that exploring young girls' self-perceptions in terms of engineering specific competencies may be possible, which could significantly impact efforts to address the gender disparity in the field.

Key words: Gender disparity; Field-specific ability beliefs; Implicit theories.

Introduction

In general, technology and engineering educational fields are male dominated (e.g. Sultan, Axell, & Hallström, 2018; Yoder, 2017). This is problematic in terms of the disciplines as a lack of diversity suggests a loss of potential talent. Additionally, from a sociocultural perspective this gender disparity indicates the existence of barriers to women entering these areas. From the perspective of enhancing technology and engineering fields, attracting and promoting diverse talent is a critical agenda to ensure their growth and prosperity. From a sociocultural perspective, it is paramount that all individuals have the opportunity to form and pursue their own aspirations without negative impacts from prejudice or bias. From both positions, there is a clear need to explore the gender imbalance in technology and engineering. A considerable amount of research has been conducted exploring gender diversity in science, technology, engineering, and mathematics (STEM), and in their review of this, Wang and Degol (2017) summarise six explanations for the existence of a gender representation gap including cognitive ability, relative cognitive strengths, occupational interests or preferences, lifestyle values or work-family balance preferences, field-specific ability beliefs, and gender-related stereotypes and biases. This paper describes the initial stages in an exploration into field-specific ability beliefs in engineering education within Ireland and Sweden, which may be able to inform technology education due to the overlap which exists in many contexts.

Much evidence indicates cultural associations between men and innate intelligence but not women (Kirkcaldy, Noack, Furnham, & Siefen, 2007; Tiedemann, 2000) and women tend to be underrepresented in fields which are considered to require innate brilliance in comparison to those where the attainment of excellence or expertise is associated with effort. These stereotypes of women underpinned the postulation of the field-specific ability beliefs hypothesis (Leslie et al., 2015) which suggests that "women may be underrepresented in academic disciplines that are thought to require such inherent aptitude" (Leslie et al., 2015, p. 262). Critically, this is not to suggest that natural ability is or is not important to certain fields in reality, rather this hypothesis is specifically associated with practitioners' opinions concerning the importance of natural ability in the field they are working in. In a large scale study, Leslie et al. (2015) tested this hypothesis against three competing hypotheses; (1) the more demanding a discipline in terms of work hours, the fewer the women, (2) the more selective a discipline, the fewer the women, and (3) the more a discipline prioritizes systemizing over empathizing, the fewer the women. The results of their study supported the field-specific ability hypothesis over the other three, and that the hypothesis extended to the underrepresentation of African Americans' as well.

There are a number of causal explanations associated with this hypothesis. In understanding these, the differences between overt/intentional and covert/subtle forms of sexism, and between hostile and benevolent forms of sexism must be considered (Swim, Aikin, Hall, & Hunter, 1995; Swim, Mallett, Russo-devosa, & Stangor, 2005; Swim & Cohen, 1997). Wang and Degol (2017) note that although overt and deliberate forms of discrimination may not be as common now as they used to be, covert and benevolent forms still exist and shape male and female career trajectories. Notably, research shows that children as young as 6 are influenced by gender stereotypes, such as that science and mathematics as male domains (Miller et al., 2014) and that boys are more likely to be "really, really smart" (Bian, Leslie, & Cimpian, 2017). One example of a causal explanation is related to perceived sense of community within fields. For example, Cheryan and Plaut (2010) found when studying English, a female-dominated field, and computer science, a male-dominated field, that "the best mediator of women's lower interest in computer science and men's lower interest in English was perceived similarity" (p.475). Furthermore, Cheryan and colleagues found that the removal of stereotypical masculine objects (e.g., Star Trek posters and video games) could increase female interest in these courses (Cheryan, Meltzoff, & Kim, 2011; Cheryan, Plaut, Davies, & Steele, 2009). Leslie et al. (2015) summarise additional causal mechanisms for the field-specific ability beliefs hypothesis eloquently, stating that:

> The practitioners of disciplines that emphasize raw aptitude may doubt that women possess this sort of aptitude and may therefore exhibit biases against them (Valian, 1998). The emphasis on raw aptitude may activate the negative stereotypes in

women’s own minds, making them vulnerable to stereotype threat (Dar-Nimrod & Heine, 2006). If women internalize the stereotypes, they may also decide that these fields are not for them (Wigfield & Eccles, 2000).

The field-specific ability beliefs hypothesis is generally linked with mindsets. Wang and Degol (2017) largely associated it with the work of Dweck and colleagues with reference to fixed and growth mindsets (Blackwell, Trzesniewski, & Dweck, 2007; Yeager & Dweck, 2012). This research reflects the implicit theories which people can have about their own or others abilities, and the capacity for these abilities to change. A similar way of considering peoples implicit theories, the elicitation of prototypical definitions (Neisser, 1979; Rosch, 1977; Rosch & Mervis, 1975; Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976), also has significant potential in this agenda. Neisser (1979, p. 182) describes the prototype of a category or concept as being ‘‘that instance (if there is one) which displays all the typical properties’’. In other words, where providing an explicit verbal definition of a construct is difficult, for example in instances where there is disagreement regarding its remit or structure, generating a prototypical definition allows for a description to be established which puts forward its typical properties as decided upon by a specific cohort of people. So while a prototypical definition may not be an objectively valid definition of a construct, it has substantial importance as it reflects the collective opinion of a specific group of people. The relationship prototypical definitions have with this area of research is that the evidence supporting the field-specific ability hypothesis considers engineering as a singular field relative to 22 other fields and innate ability as a singular construct (Leslie et al., 2015). There is therefore now a need to determine not only the differences between how males and females of varying ages view themselves and their gender groups in terms of innate intelligence for engineering, but also what does this mean when associated with engineering.

Purpose

The purpose of this study is to initiate an investigation into the field-specific ability beliefs hypothesis in engineering and technology education so as to put forward an additional attempt at addressing gender disparities. In doing this, there is a clear need to determine what personal characteristics are associated with innate intelligence in the context of engineering, with specific emphasis on identifying potential characteristics which are dissociable between engineering and other fields. In previous work, Sternberg, Conway, Ketron and Bernstein (1981) examined the prototypical definition of intelligence in experts and laypeople. Both cohorts conceived intelligence as having three components. For experts these consisted of verbal intelligence, problem-solving ability, and practical intelligence while for laypeople consisted of practical problem-solving ability, verbal ability, and social competence. Interestingly, there were two common factors, verbal ability and problem solving ability, with a third factor differentiating the cohorts and reflecting a cohort specific form of practical intelligence describing a set of behaviours important specifically but not exclusively within each demographics cultural context. Subsequent work by Buckley et al. (2019) adopted the method used by Sternberg et al. (1981) in the context of STEM education with initial technology teacher education students. Similarly, the studied cohort also found intelligence in the context of STEM education to consist of three components, termed social, general and technological competences. The general competence factor found by Buckley et al. (2019) largely mirrors the problem-solving ability factor found by Sternberg et al. (1981), with their social competence and verbal ability/intelligence factors also sharing some overlap. Interestingly, the third factor found by Buckley et al. (2019) also appears to be cohort specific and notably had the largest factor loading on the cohorts implicit theory of intelligence. Together, these studies add support for Sternberg's (1984) postulation of a ‘common core’ of intellectual functions which are culturally shared. In other words, that there are certain intellectual behaviours more associated with being human in general than with operating in any specific discipline. The purpose of this study is to instigate an investigation into determining both sets of intellectual functions for engineering, so as they can be studied in greater detail with non-practitioners.

Method

Approach and design

The method establish by Sternberg et al. (1981) and subsequently adopted by Buckley et al. (2019) was utilised in this study. The entire method involves the use of two separate and sequential surveys, however this paper reports only the results from the first of these for this study.

In considering engineering as a single field to reflect the work of Leslie et al. (2015), two variables need to be considered particularly as it concerns gender disparities. First, there are a number of engineering fields, and they don't all display the same gender ratios. Taking the USA as an example, Yoder (2017) reported that in relation to 23 fields of engineering, at bachelor's level female representation ranged from 12.5% to 50%, at master's level is ranged from 13.6% to 45.7%, and at doctoral level it ranged from 10.7% to 48.7%. Therefore, while engineering is being considered as a singular, representation from a variety of engineering disciplines is important. Second, data from the Organization for Economic Co-operation and Development (OECD) indicates that the percentage of females enrolled in "engineering and engineering trades" education at bachelor's, master's and doctoral level ranges from 11.54% to 28.33% in OECD countries (OECD, 2019) suggesting that there is a cultural factor that needs to be explored. Therefore, it is necessary to considered multiple countries to explore cultural variances.

In the first survey, random participants from within a purposely selected cohort are first asked for demographic information to ensure alignment with the pertinent research question, and then asked giving a single request to list behaviours characteristic within intelligence in the relevant field. In this instance, the exact wording was "Please list all of the characteristics or qualities of a person you would describe as intelligent in the context of engineering". For the second survey, for which the data is currently being collected, the survey is sent to a random sample from within the same demographic of participants. The same demographic questions are asked, however this time the survey contains a list of each unique characteristic mentioned in the responses to the first survey, with participants being asked to rank each one on a 5-point Likert scale with the ratings ''1 - Not important at all'', ''2 - Unimportant'', ''3 - Neither important nor unimportant'', ''4 - Important'', and ''5 - Very important''. In this instance, the exact word used was ''please rate how important each of these characteristics are in defining 'your' conception/understanding of an intelligent engineer".

Implementation and participants

Based on the 2016 OECD data (OECD, 2019), Sweden has the highest representation of female engagement with engineering in higher level education (28.33%), while Ireland has one of the lowest (14.13%). They were therefore selected as if a cultural effect is to be seen in terms of gender perceptions, they provide opportune contexts to explore it and to base future work in.

In Sweden, the first survey was sent to a random sample of 2000 engineering students in the country's largest university level engineering education provider. A total of 174 students responded to the survey (M_{age} = 20.81, SD_{age} = 2.23), of which 122 were male, 50 were female and 2 chose not to disclose their gender. The participants came from a variety of engineering sub-disciplines including 57 from IT and computer technology, 52 from mechanical engineering, industrial technology and finance, 14 from architecture, community building and construction technology, 13 from vehicle engineering, 11 from a common entry programme, 10 from energy and environment, 7 from electrical engineering, technical physics and applied mathematics, 6 from design and product development, 3 from technology and learning, and 1 from medical technology. Each participant was on a five-year long programme where the first three are at honours bachelor level and there is an automatic transition in year four to master's level for the final two years. Of the sample, 141 were in their first year of study, 29 in their second, 3 in their third and one respondent was in their fifth year.

In Ireland, the survey was sent to engineering students in two higher education institutions, one university and one institute of technology, to reflect the two types of providers of engineering education in the country. In the university, the survey was sent to approximately 600 students. A total of 85 students responded (M_{age} = 20.51, SD_{age} = 3.18), of which 65 were male, 19 were female and 1 chose not to specify their gender. The participants came from a number of different engineering sub-disciplines including 22 from mechanical engineering, 20 from engineering management, 18 from civil engineering, 11 from industrial engineering, 8 from biomedical engineering, 3 from product design engineering, 2 from aeronautical engineering, and 1 from electrical engineering. 80 of the participants were from honours bachelor's programmes, with 3 studying on ordinary bachelor's level programmes, and 2 studying at master's level. Finally, 28 participants were in their first year of study, 36 were in their second year, 7 were in their third year and 14 were in their fourth year.

In the institute of technology, the survey was sent to approximately 800 students. A total of 77 students responded (M_{age} = 27.32, SD_{age} = 9.01), of which 56 were male and 21 were female. 27 participants came from software engineering, 15 came from electronics and computer engineering, 11 from civil engineering, 8 from mechanical engineering, 7 from polymer engineering, 4 from quantity surveying, 2 from engineering management, 2 from mechatronics, and 1 from industrial engineering. 4 participants were studying on programmes where the degree award was a higher certificate, 26 students were studying on ordinary level bachelor's programmes, 42 were from honours bachelor's programmes, a further 4 were studying at master's level, and 1 participant was a doctoral candidate. Finally, 21 participants were in their first year of study, 17 were in their second, 19 in their third, 17 in their fourth and 3 were in their fifth.

Results

The first stage of the analysis involved coding each of the characteristics offered by participants. The list generated from the Swedish sample was initially coded with an inductive approach and subsequently the generated codes were used to deductively code the list generated by the Irish sample. A list of 683 characteristics (M = 3.93, SD = 3.13) was generated from the Swedish participants. A total of 445 remained once literal duplicates were removed. The characteristics were primarily coded by two members of the research team. Initially one researcher coded all of the data by manually collating each of the 445 characteristics into groups based on the similarity of their wording, which resulted in a total of 81 unique codes being created. A second researcher then reviewed each of the codes and commented on their uniqueness within the list. At this stage, the second researcher identified eight of the codes, i.e. four pairs, as synonyms. These were reviewed collectively by both researchers and four codes were revised to clarify their distinctions. For the second stage, the first researcher reviewed each of the characteristics they had coded again based on the revisions to the codes while the second researcher independently coded each of the 445 characteristics using the established coding scheme. When compared, there were 17 discrepancies indicating a 96.18% level of agreement between the researchers when applying the codes. Finally, a third member of the research team coded each of the 17 discrepancies to aid in assigning their final codes.

A similar process was conducted with the data from the Irish sample. A list of 619 characteristics (M = 3.80, SD = 1.91) were generated, with 342 remaining once literal duplicates were removed. Both the first and second researcher independently applied the coding scheme generated from the Swedish data to the list of 342 characteristics. When compared there were six discrepancies, indicated a 98.25% level of agreement. Both researchers agreed that there were 15 characteristics for which existing codes would not suffice. They collectively created 9 new codes, which the third researcher reviewed and confirmed. Therefore, a total of 90 unique codes, representing 90 unique characteristics of an intelligent engineer, were generated from the survey results (Table 1).

Table 1. Codebook with sample characteristics.

Code	**Example statements**
Ability to apply knowledge	Knowledge of how to apply what you have learned; Ability to apply theoretical knowledge to practical problems.
Ability to find relevant information	The ability to find information; Know where to find sought-after information.
Able to multitask	Good at multitasking.
Able to think abstractly	Abstraction; Good ability to think abstract; Able to abstract problems so that they become more gripable.
Able to understand complex information	Ability to understand complicated relationships; Understand so well that it can account for an understandable explanation; Able to decode information.
Adaptable	Adaptability; Adaptive; Can adapt; Flexible.
*Aggressive	Aggressive.
Ambitious	Ambitious.
Analytical	Analytical; Analytical ability; Break down complex systems into smaller components that can be more easily analysed.
Can make complex systems	Be able to create complicated systems.
Cautious	Prevention; Consider before doing anything.
Charismatic	Charisma; Charismatic.
Competent in mathematics	Good knowledge in mathematics; Good at mathematics.
*Competent in mechanics	Mechanics; Understanding of mechanics.
Competent in physics	Physicist; Basic knowledge in physics.
Competent in science	Mediation of science; Scientific.
Competent in technology	Good at technology; Technically talented.
Competitive	Competitive; Fighting spirit.
Confident	Self-confidence; Confident.
Craft skill	Good "craft" ability; Good practical skills.
Creative	Creativity; Creative thinking; easy to get many quick ideas others would call creative.
Creatively brave	Fearless to test solutions; Dare to stretch the boundaries.
Critical thinking	Source critical; Critical; Critical thinking.
Curious	Curious; Curiosity.
Decision making skills	Ability to make difficult decisions; Actionable; Good estimates.

Code	Example statements
Dedicated	Dedication; Dedicated; Perseverance.
Desire to learn	Constantly learn more/develop; The quest to always continue to learn/develop; Willing to learn; Develop their thinking for the better all the time.
Detail orientated	Meticulous; Accuracy; Eye for detail; Feeling for detail.
Determined	Determined; Determination.
Diligent	Documents the work carefully; Diligent.
Disciplined	Discipline; Disciplined; Focussed.
*Disorganised	Disorganised.
*Easily bored	Easy gets bored.
Economic	Economic.
Educated	Educated.
Efficient	Efficiency; Effective/efficient.
Empathetic	Ability to understand the needs of others; Can "get acquainted with the shoes of others" for understanding several perspectives.
Ethical	Can put their work in an ethical perspective; Morality.
Field specific knowledge	In-depth knowledge in the field; Knowledgeable in their field of work; Expertise in the subject area.
Foresight	Long-term-thinking; See problems before it arises
*Funny	Funny; Have a sense of humour; Witty.
General knowledge	Generally formed/generally knowledgeable; Broad knowledge.
Good at learning	Ability to effectively absorb new knowledge; Ability to familiarize themselves with new systems; Knowledge acquisition; Fast learner.
Good collaborator	Good at working in groups and projects; Collaborative.
Good communicator	Ability to communicate technology in an understandable way; Good communication; Communication skills.
Good social skills	Social skills; Socially competent; EQ; Social ability.
Good work ethic	Good work ethics; Productive.
Has a variety of areas of interest	Has one or more hobby, Likes to contribute in many areas.
Have a large contact network	Large contact network.
Healthy	Healthy.
*Honest	Honest.
Humble	Humble; Prestigeless.
Independent	Own thinking/Able to have own ideas; Independence; Self-propelled.
Intelligent	Whiz-kid; IQ; High IQ; Clever; Smart.
Interested in engineering	Deep interest in their area; Interested in their profession/area; Technically interested.

Code	Example statements
Intuitive	Intuitive; Strong intuition for the relevant subject.
*Lacking social skills	Lack of social skills.
Lazy	Lazy; Do not always study.
Leadership skills	Leadership.
Logical	Good on logical thinking; Logic; Rational.
Mature	Mature.
Methodical	Methodical; Structured; Systematic.
Motivated	Motivation; Motivated; Enthusiastic; Passionate; Driving.
Nerdy	Nerdy.
Nice	Nice; Friendly.
Open minded	Openness; Open to criticism; Open minded.
Organised	Determine how to plan; Ability to plan own work; Well prepared; Organized.
Pessimistic	Someone who is a bit pessimistic (good for prevention of errors).
Positive	Belief in the future; Positive; Positive towards challenges.
Practically orientated	Thing orientated; Inventive; Practical.
*Pragmatic	Hands on; Pragmatic.
Problem solving	Good problem solving ability; Good problem solver; Effective problem solving.
Quick thinking	Fast thinking; Quick; Quick ideas; Quick understanding.
Quiet	Quiet.
Realistic	Adds perspective in discussions; Realistic.
Reasonable	Reasonable; Can settle disputes.
Reflective	Reflective
Reliable	Reliable; Time-conscious; Consistent.
Resourceful	Resourcefullness; Improvisation ability.
Responsible	Responsible; Takes on great responsibility.
Self-aware	Knowing what it is you cannot do and then able ask someone who knows about help; Don't take on things that they cannot handle.
Self-control	Stress management; Patience; Stable; Maintains concentration even when not understood.
Solution orientated	Target focussed; Solution orientated; Impact thinking; Solution focussed.
Spatial ability	Spatial intelligence; Spatial understanding; Three and multidimensional thinking and visualizing.
*Strange	Strange.
Stressed	Stressed.
Stubborn	Stubborn.
Supportive	Helps and lifts (encourages) other workers; Supporting;

Code	Example statements
	Appropriate guidance; Unselfish.
Thoughtful	Thoughtful; Deep thinking.
Visionary	Vision; Can see an overall picture; Have future vision and see opportunities.

Note: * = Code created when coding the data from the Irish sample.

It is important to note at this point that in the full method, where both surveys are used, as the first survey dictates the design of the second each code is considered to be of equal importance regardless of its frequency of occurance. However, as only the results of the first survey are presented, frequencies of codes are considered in this paper.

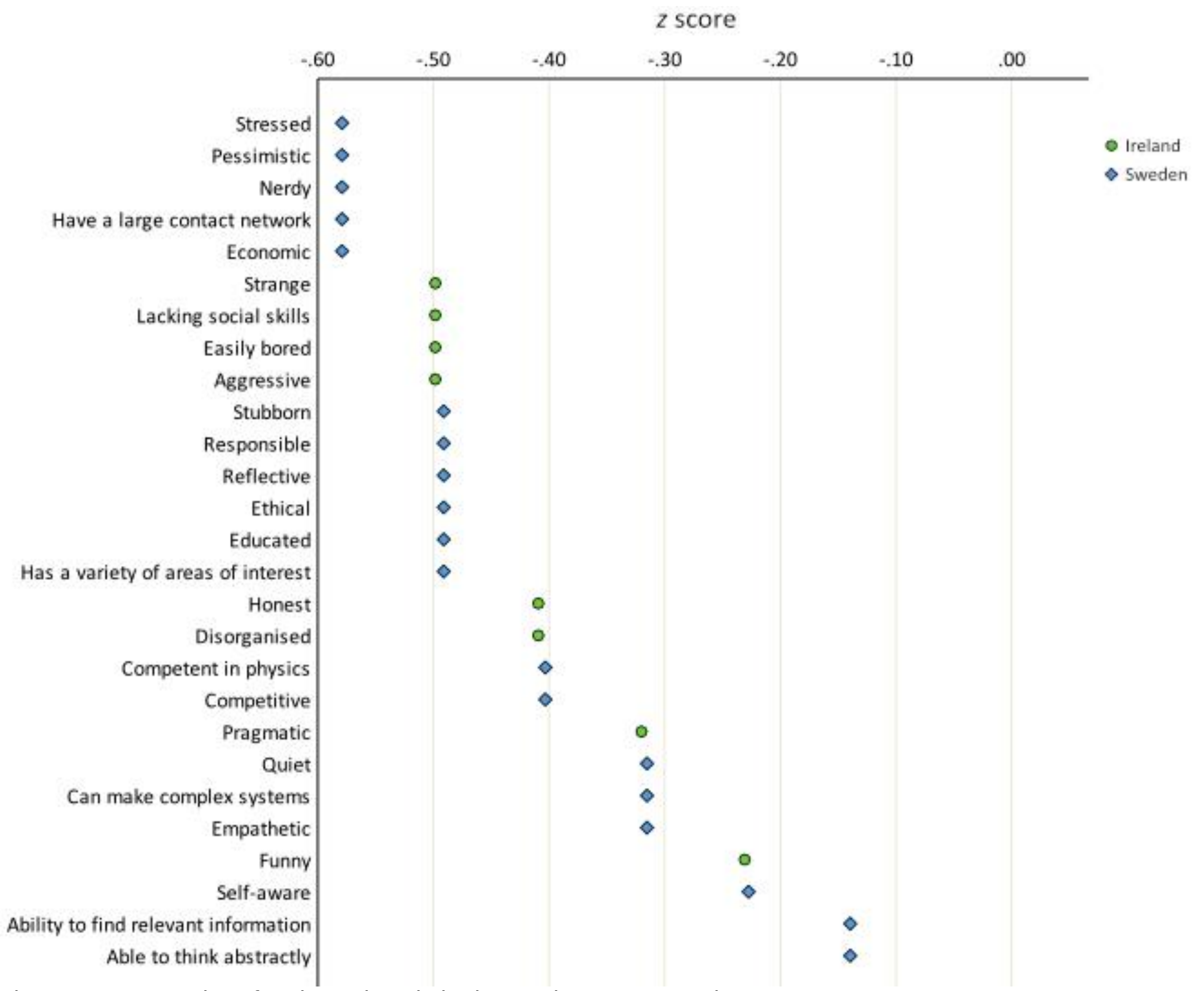

Figure 1. Frequencies of codes unique in both samples represented as z-scores.

Figure 2. Frequencies of codes common to both samples represented as z-scores.

The frequencies of each codes were considered in terms of the complete lists of 683 characteristics from the Swedish sample and 619 from the Irish sample. In order to compare both lists frequencies were converted to z-scores. As both lists had different means and standard deviations, they were first transformed to have a mean of 0 and a standard deviation of 15. Figure 2illustrates the frequencies of codes that were common in from both lists in terms of z-scores, and Figure 1 illustrates the unique codes from each sample in terms of z-scores.

Discussion

It is of most interest to consider the results from two related perspectives; how they relate to the previous work conducted by Buckley et al. (2019) and Sternberg et al. (1981) in terms of identifying engineering specific competencies, and what are the differentiating codes from each country.

In terms of the unique codes for each country, it should be noted from the position of frequencies that no unique code occurred a statistically significant number of times, i.e., there were no z-scores less than -1.645 or greater than 1.645. The codes primarily relate to personality characteristics, for example stressed, pessimistic, nerdy, economic etc. and considering the method, it is conceivable for an intelligent person to have any personality. Therefore, it is arguable that the codes associated with abilities are more important, of which there were none of from the Irish sample suggesting that data saturation was achieved with respect to the two cultures. In terms of unique abilities, the Swedish sample generated codes including “able to think abstractly”, “ability to find relevant information”, “can make complex systems”, and “competent in physics”. The first two of these are similar to codes found by Buckley et al. (2019) in that they relate to problem solving. The second two however are unique in comparison to both the work of Buckley et al. (2019) and Sternberg et al. (1981) suggesting competencies which may be uniquely considered to relate to engineering.

Considering the common codes, those that occurred a statistically significant number of times include “problem solving”, “creative”, “logical”, “good communicator” and “competent in mathematics” suggesting that these may be have the strongest associations with engineering, however this does not mean that they are uniquely perceived as associated with engineering. When compared to the work of Buckley et al. (2019) and Sternberg et al. (1981), many of the codes theoretically fit the factors that they identified. The codes which appear unique to engineering seem to be associated with disciplinary knowledge, for example “field specific knowledge”, “competent in science”, “competent in mechanics”, “competent in mathematics” and “competence in physics”. When considered in relation to the technological competence factor observed by Buckley et al. (2019), this suggests that, from the perspective of implicit theories, the differentiation characteristic between technology and engineering is one of knowledge and not activity, as both datasets emphasise general problem solving and creativity. Potentially, although it cannot be confidently inferred from this data, the type of activity may also be implicitly perceived to be different, as craft was seen as important in a technological context whereas it has a low frequency in the current dataset. The results of the second survey will add additional empirical data for which to deduce this from.

Finally, the frequencies of the common codes suggest a cultural difference in the perceptions of intelligent engineers. Based on the frequencies, Swedish participants were more likely to associate intelligent engineers with general competencies such as being “solution orientated, visionary”, “good at learning” and having “general knowledge”. However, the biggest difference in terms of a high frequency from the Irish participants was to associate an intelligent engineer with someone who is good at mathematics. The second biggest difference in this regard was the frequencies for the “good communicator” code, suggesting that for the Irish participants, communication was a more important trait for an engineering than what was perceived by Swedish participants.

In conclusion, the results of this study suggest that engineering likely has a unique characteristic in terms of engineering competency, and that is it probably knowledge based and the interpretation of craft in engineering education may be different to that in technology education. In terms of future work regarding gender differences, this suggests that exploring young girls' self-perceptions in terms of engineering specific competencies may be possible, which could significantly impact efforts to address the gender disparity in the field.

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