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An Examination of Individual Attributes and their Impact on Team Creative Design Outputs*

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While teaming is a vital component of engineering, it is important to remember that there is no team without individuals, and individual behavior can drive team outputs. One of the individual factors that may manifest itself at the team level is individual risk-taking attitudes, which can be impacted by personality and preferences for creativity. However, a gap exists in research on the impact of team composition in these factors on creative outputs, as previous research has found that team composition plays a key role in team performance. The current work builds upon a previous work, and was developed to examine how the diversity of team personality and preferences for creativity impact the likelihood of concept screening events falling into one of the four categories of Signal Detection Theory. The results of this study show that for the population studied here, no team with the same composition was able to obtain "good" decisions in all four categories (increased hit, decreased Type I error, decreased Type II error, increased correct rejections). The team compositions studied here were only related to the likelihood of making good decisions in two or three of the four categories. This serves as empirical evidence supporting the complicated nature of the impact of team composition and provides some support for educators and instructors for a better understanding of team creative performance.

Keywords: design education, design methodology, design teams, design theory, design theory and methodology

1. Introduction

In a survey with more than 3,000 CEOs, IBM identified innovation and collaboration as the essential paths forward for businesses, stating that together they offer "access to broader ideas, talent, and opportunity" [1, 2]. This is why larger corporations like Google, Amazon, and Pixar have made a conscious effort to establish a culture that accepts and promotes creative and novel problem-solving methods [3] and why companies like Wikipedia and Mozilla rely heavily on the contribution resulting from collaboration [4]. Diego Rodriguez, a partner at IDEO, argued that organizations should take full advantage of having multiple smart people working on one problem [4] because innovation and teamwork are the keys companies need to open opportunities in new and existing markets and improve market payoffs [5].

The focus on innovation has been attributed to its ability to help companies achieve competitive advantage in the market, maintain market dominance [6], and gain leadership status in that new market [7, 8]. This is partly achieved through engagement in radical innovation, which produces concepts that are drastically different from existing concepts [9, 10]. However, while having the potential to achieve the goal of company expansion and dominance, radical innovation can also result in high uncertainty of future success [11–14] and potentially difficult development [9, 15]. This high uncertainty associated with radical innovation often leads companies to be biased against these ideas due to a lack of more immediate, certain, and foreseeable outcomes [15, 16]. However, although the decision to choose less risky and less radically innovative designs may seem economically viable, in the long run, it also means that companies are giving up the opportunity to make groundbreaking innovations [17]. One of the strategies intended to better promote radical innovation is with the use of more design teams.

Working in teams is seen as a benefit over individual-level contributions because the "wisdom of the collective" can help a team perform above and beyond the sum of its individual members [18–21]. This was further supported by the work of Hoffman, et al. [22], where the authors noted that heterogeneity or differences within the team allowed members to make decisions based on different sources of information based on their background and experiences, which can enable better team decision-making outcomes. This is particularly true for engineering, where the collective can help to improve performance in complex tasks by offering a diversity of opinions [20, 23, 24],

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experiences [25–29], and knowledge [25, 29–31] that are necessary for the development of paradigm-shifting innovations. As such, fields relating to engineering have shown a higher tendency to use teams as units of problem-solving [32], and there has been a push in both the workforce and academia for engineers to adapt and acquire teamwork skills [33].

However, teamwork does not always lead to good outcomes. Researchers have identified both a positive [34–37] and a negative [38–41] linkage between teamwork and ideation. On the positive side, researchers have found that teams develop both more concepts and higher quality concepts [14, 42]. Working in a team setting has also been found to help avoid confirmation bias [23] and fixation bias [23, 24], allowing the team to explore and consider more aspects of the problem. On the negative side, teamwork has been shown to negatively impact the number of ideas produced in comparison to individuals [41]. Specifically, in terms of idea generation, a study has found engineers generate fewer ideas in a group when compared with a group of an equal number of individuals working alone [41]. Team construction can also lead to social comparison and lack of identification, which may result in social loafing or the inhibition of creative outputs [43–45].

Therefore, a gap exists in research in terms of examining team composition that can optimize their performance for radical innovation – more specifically, help teams avoid one of the two fatal errors: Type I and Type II errors [46]. Here, Type I and Type II errors are modified to fit the creative engineering design and risk-taking context of this paper, where Type I error refers to when decision makers neglect a good idea [47], and Type II error refers to accepting a 'bad' idea and investing scarce resources in a project that would be unsuccessful [48]. All references to Type I and Type II errors in this paper are based on this definition unless otherwise stated.

However, the mechanism behind team performance is very complex, as indicated by the variety in their outputs. Studies have found that performance and decision-making within a team can be hindered by many factors such as work preference [38, 40, 41], perception of the environment to be safe for taking creative risks [49], team communication [50], and individual lack of identification with the team [18, 45, 51–53], lack of cooperation, lack of confidence, and personal problems [33]. Other individual attributes, such as personality and cognitive attributes have also been found to influence the group [54]. One factor that contributes to a lack in this area of research is that conducting team-based research is difficult, as traditional methods of human-subject-based testing are difficult to achieve the population required for large-scale team-level studies, which limits team-level examinations [55-57]. An preliminary step toward this direction is to look at individual contributions to the team – after all, there is no team without individual team members, and research has shown that individual behavior and attitudes can drive team outputs [58]; and understanding how individual team member attributes manifest themselves in team performance may help to add to our understanding of teams and their performances. This method was also used by a previous study by Peng, et al. [59], which this paper builds off of.

Therefore, the goal of this paper was to examine if simulated team composition of personality and preferences for creativity based on individual data can be used to predict performance during concept screening for radical innovation. Although this method of simulation does not capture more complicated interpersonal interactions, using individual data to simulate team data can still serve as an initial step toward examining team composition and its impact on team performance. More specifically, this study sought to examine what could influence the probability of concept screening events falling into one of the modified signal detection theory categories: (1) hit (correct identification of a good idea) (2) Type I error (not choose good idea), (3) Type II error (choose bad idea), and (4) correct rejection. This was achieved through an exploration of the relationship between (1) diversity of personality (2) diversity of preferences for creativity and the probability of a concept screening event falling into one of the four signal detection theory categories in simulated teams. The results of this study provide some insights into the role of individual attributes on team-level performance.

2. Related Works

Studies have found that team formation can help promote creativity, cooperation and design outcomes [18, 51, 60]. This is important since the ability to make creative and innovative contributions is a trait that has become increasingly valuable [61, 62]. However, due to the risky nature of creativity [63] and the risk-averse nature of humans [64–66], people tend to avoid generating and selecting creative alternatives because of the risks associated with them. This is especially true for the engineering profession, where individuals usually avoid risk-taking to reduce the potential negative consequences that can result in physical harm [67]. This work seeks to investigate ways to help promote correct design risk taking, specifically through team composition. The remainder of this section outlines relevant literature that lays the foundation for the current work.

2.1 Personality and their Influences on the Effectiveness of Creative Decision-Making

One of the key factors that can impact team performance is personality composition. For example, Muchinsky and Monahan [68] established two models to explain how the composition of team members' personalities impacts the team's performance [68, 69]. The first model (complimentary model) suggested that teams who have heterogeneous (i.e., diverse) personality attributes performed better because team members were able to bring their unique contributions to the team [68–71]. These advantages might be because diverse personalities might lead to a wider variety of expertise as compared to more homogeneous groups [72–74]. On the other hand, the supplementary model proposed by Muchinsky and Monahan [68] suggested that homogeneous (i.e., similar) teams might see higher performance than heterogeneous [68–71]. They attributed this to an elevated sense of belonging, as the members perceived themselves to have similar values and interests as the rest of the group [68, 69]. These models helped to show that the diversity of team personality could be related to performance at a team level, which was why this would be a measure used as part of the evaluation for this study. This finding was supported by a study done by De Cooman et al., where they found complementary and supplementary person-team fit to contribute positively to team effectiveness [70].

Specifically relating to creativity and creative decision-making, personality had been found to be related to the ability to make creative contributions [75]. It is important to note that risk has been identified as a fundamental part of creativity, as being creative meant taking a step into the unknown – breaking rules, challenging authority, and taking risks [63]. Therefore, much literature has investigated not only creativity but also creative risk-taking. More specifically, studies have found that personality, as measured by the big five factors of personality (FFM) framework [76], is empirically linked to creativity [75, 77–82]. The five factors summarized in the model were: extraversion, agreeableness, neuroticism, conscientiousness, and openness [83, 84], with each factor evaluating a slightly different aspect of personality. One of the metrics used to quantify personality and see how it fits into the five-factor model was the mini-IPIP survey, which is a shortened version of the IPIP-NEO (International Personality Item Pool Representation of the NEO PI-RTM) [83].

Extraversion is the tendency of the individual to be enthusiastic and outgoing socially, while also seeking novelty and enjoying exploratory activities [85–88]. Extraversion also encompasses interpersonal engagement [87], which would be related to performance in teams. Extraversion has been found to be negatively correlated with individual levels of risk aversion [89], where extroverts have been found to prefer higher risk [90]. On the other hand, agreeableness examines the tendency of individuals to be accepting and trusting [85]. Those with higher agreeableness can be more willing to conform and avoid possible conflict [91]. This also leads individuals high in agreeableness to be less motivated towards generating novel and creative ideas [85, 92]. The third factor of the personality model is conscientiousness, which measures the level of self-discipline and obedience in an individual [86]. Highly conscientious individuals can focus more on achieving accomplishments and prefer sticking to a plan [86]. This could be the reason why conscientious individuals are also more risk-averse [89], supported by literature finding low conscientiousness individuals to be more likely to engage in reckless risk-taking [93]. Neuroticism on the other hand, is associated with a lack of emotional stability [94] and can more easily experience negative emotions such as insecurity, shame, or stress in general [91, 95]. In terms of risk-taking, more neurotic individuals are found to be more risk-averse [89]. However, this relationship is not uniformly found, as research has also discovered that high neuroticism can be linked to greater reckless risk-taking [93], which may lead to accidents and fatalities [96]. Lastly, openness examines the individual's curiosity and variety of experiences [86]. Higher levels of openness were found to be positively related to the likelihood of taking risks [97, 98].

At a team level, previous research has found that individual attributes can interact with each other in a complicated manner, which results in the team-level attributes being more than simply an aggregation of member attributes [99]. Therefore, research is needed to see if and exactly in what way team personality composition can affect the team's creative outputs. More importantly, it was found that the relationship between personality and creativity can sometimes change when shifting from looking at an individual level to a team level, although only some of the five factors have been found to have an impact. More specifically, agreeableness, which has been found at an individual level to be negatively correlated with creativity, actually promotes creativity at a team level by leading to a higher probability that a novel idea is selected to pass the concept screening [80]. Previous research has also identified it as a key factor in group creativity [100]. On the other hand, at a team level, the impact of conscientiousness stayed relatively the same, with higher conscientiousness leading to a tendency to select more novel ideas for further development [80, 81]. The factor of openness has been found to be negatively correlated with a display of creativity at a team level, where lower openness scores have been related to the selection of more novel and quality ideas [81]. These studies help to show that there is a strong relationship between personality and creative tendencies at an individual and team level. However, there is a lack of research that investigates how individual personality manifesting in team composition can contribute to the teams' preferences. This is because prior works in this area still examined the relationship individually but in a team context [80, 81].

2.2 Risk-taking Preferences and their Influence on the Effectiveness of Creative Design Decision-making

In addition to personality, another individual attribute that can influence the creative risk-taking tendencies of individuals is their preference for creativity. The importance of studying these attributes is that even if creative ideas were generated, they would still have to make it through concept screening in order for it to have a chance of making it to the market [101, 102]. However, depending on the subjective preferences and biases that the decision-makers may possess, these innovative ideas might fail to pass concept screening [103, 104], resulting in a lost opportunity for radical innovation. The most prominent subjective preferences or biases that might influence decisions in this area are the creative risk-taking preferences of the decision-maker [105, 106]. Therefore, in order to better capture this preference, the Preference for Creativity Scale (PCS) was used. This metric was developed by Toh and Miller [107] and it categorizes this preference into four categories: team centrality and influence, risk tolerance, creative confidence and preference, and motivation. The four factors of PCS each measure slightly different aspects of the preferences for creativity.

The first factor modeled by PCS is *team centrality and influence (CTI)* which focuses on assessing team dynamics and how members can influence the team's preference for creativity. It does so by examining individuals' motivation to display creative tendencies in a team environment [108], fear of rejection and failure [43], freedom to express opinions [22], and sense of self and confidence [109], which have all been found to influence the individuals' willingness to generate and select creative ideas. In addition, this factor also measures the amount of freedom individuals have within the team to freely express their ideas [22], and how much the individual can influence the team decision [108]. This factor can also play a role in influencing the team environment.

The second factor modeled is *risk tolerance (RT)* which focuses on the willingness of the individual to participate in risk taking [81]. More specifically, it examines the optimism [110], ambiguity aversion preferences [111, 112], risk preferences [113–115], propensity to take risks based on previous experience [113, 116], and outcome history previous risky decisions [113, 116]. These factors were included in the construction of the risk tolerance factor because previous research has shown they can impact the perception, and ultimately the preferences for the creativity of an individual [107].

The third factor modeled is *creative confidence and preference* (CC). This factor focuses on individuals' preferences for creativity during the creative design process, and their confidence in bringing their ideas to life [81]. This factors examine individuals' preferences for feasible ideas [106], and confidence in their ability and intention to produce creative, novel, and original ideas [117]. This confidence is important for being creative in a work environment [117].

The fourth factor modeled is *motivation* and focuses on the individual's motivation to complete the task [81]. This factor includes the following aspects: intrinsic motivation to perform and complete the task [118], sensitivity to criticism and discouragement [119], and sensitivity to assessment by superiors [120]. Although previous research has been done that uses the PCS to investigate individual preferences for creativity in the creative performance [81], there has yet to be an investigation looking at how the team-level preference can impact the team-level creative outputs in terms of the accuracy of the ideas in relation to signal detection.

In their previous works, Peng and Miller [121, 122] investigated the use of Signal Detection Theory (SDT) in the context of creative design outputs to examine the impact of individual attributes on the likelihood of concept screening events to fall into the four signals. In its original mode, Signal Detection Theory (SDT) examines whether the signal (e.g., radical idea that can lead to market success and is high quality) is identified with the presence of noise (e.g., radical ideas that will fail and is low quality, and can cost a lot of money) [123, 124]. This identification is done with a human observer, and the final decision can be made based on two factors: (1) the information presented during the event, and (2) the subjective decision of the observer on the event [124]. Then, based on the event, the decision made by the human observer can fall into one of the four categories [123]. However, in for both the previous studies and this study, the four categories of SDT were modified slightly to the context of creative design, where the signal is now the quality of the idea, and the observation was whether the decision maker allowed that idea to pass concept screening. In their work, Peng and Miller [121, 122] found that individual attributes like personality and creative preferences were able to predict the likelihood of concept screening events to fall into some of the categories of SDT. However, it is not known if similar or different trends might be found at the team level, when team composition of the characteristics would be taken into account. This gap in research is what fueled this current work.

3. Research Questions

The goal of the current work was to determine the impact of team composition of personality and creative preferences on the effectiveness of the team in making decisions during concept screening. Specifically, it does so by examining the following research questions (RQ) aimed to understand *how team composition in terms of diversity of personality or Preferences for Creativity (PCS) factors influence*:

RQ 1: the likelihood of hit occurring in radical innovation tasks?

This research question was constructed to examine the impact of team composition of personality and preferences for creativity of the evaluator on the likelihood of an evaluation falling in the hit (i.e., correct selection) category for radical innovation. Our hypothesis was that diverse teams in personality and PCS would be related to a higher likelihood of hit occurring. This hypothesis was based on previous literature that found teams with a moderate level of "conflict" to result in more discussion [50]. And that variety in emotions [89] and curiosity [97, 98] would improve the team's performance and result in them not being biased solely by aspects such as the novelty of the ideas or the team environment.

RQ 2: the likelihood of Type I error occurring in radical innovation tasks?

This research question was constructed to examine the impact of team composition of personality and preferences for creativity on the likelihood of an evaluation falling in the Type I error (i.e., missing a high-quality idea) category for radical innovation. Our hypothesis was that less diverse teams in personality and PCS would be related to a higher likelihood of Type I error occurring. This hypothesis was formed based on prior work that found that teams that (1) are too high, too low, or have no "conflict" [50], (2) lack disagreement regarding the plan [85, 92], (3) are too similar in their emotional state [89], or (4) having the same level of curiosity [97, 98] can hinder team identification and communication, thus resulting in worse performance and a higher likelihood of making errors.

RQ 3: the likelihood of Type II error occurring in radical innovation tasks?

This research question was constructed to examine the impact of team composition of personality and preferences for creativity of the evaluator on the likelihood of an evaluation falling in the Type II error (i.e., selecting a low-quality idea) category for radical innovation. Our hypothesis is that less diverse teams in personality and PCS would be related to a higher likelihood of Type II error occurring. This hypothesis was formed based on prior work that found that teams that (1) are too high, too low, or have no "conflict"[50], (2) lack disagreement regarding the plan [85, 92], (3) are too similar in their emotional state [89], or (4) having the same level of curiosity [97, 98] can hinder team identification and communication, thus resulting in worse performance and a higher likelihood of making errors.

RQ 4: the likelihood of miss occurring in radical innovation tasks?

This research question was constructed to examine the impact of team composition of personality and preferences for creativity of the evaluator on the likelihood of an evaluation falling in the correct rejection category for radical innovation. Our hypothesis is that diverse teams in personality and PCS would be related to a higher likelihood of correct rejection occurring. This hypothesis was formed based on prior research which found that a moderate level of "conflict" [50], variety in emotions [89], and variety of curiosity [97, 98] would benefit the team's performance and not result in them being significantly biased by aspects such as the novelty of the ideas or the team environment.

4. Methodology

The goal of this paper was to identify the impact of team composition (personality and preferences for creativity) on the likelihood of an idea evaluation falling into the four categories SDT categories (i.e., "Hit", Type I error, Type II error, and Correct Rejection) for radical innovation. The methodology presented here illustrates how teams were simulated from data collected over a span of two years [81] and previously accessed on the individual level in a previous study by Toh and Miller [81], Peng and Miller [121], Peng and Miller [122]. A

Table 1. Breakdown of simulated teams

Design Problem	Course section	Number of Participants	Number of Simulated Teams
Pedestrian Accidents	8	16	1820
	9	30	27405
	10	29	23751

slightly different team composition impact was also completed by Peng, et al. [59]. We seek to further this previous effort with the completion of this paper. Here, we present the aspects of the methodology pertinent to the current investigation and discuss the metrics used to analyze the simulated teams' performance during concept generation and screening. In the following sub-sections of the Methodology, information on these studies that pertain to this current work is described.

4.1 Participants

This study utilized a total of 75 participants that were used for simulation. They were from three different course sections, but all completed the same design prompt which are discussed in detail in Toh and Miller [81]. In brief, the task was to address a systems problem (pedestrian accidents on campus). The number of participants and teams as well as the course section can be found in Table 1. The participant data used for this study were originally gathered during a study by Toh and Miller [81], where students were recruited from undergraduate engineering design courses at a large Northeastern university. All participants were assigned to three-four-person teams by their course instructors at the start of the semester. The data was combed through and anyone with missing data points was excluded from this study. In addition, only the idea-level data with novelty, quality, concept screening, class, and task information were kept in the final analyses.

4.2 Procedure

In their study, Toh and Miller [81] separated the study into two phases to better examine the effect of the Preferences for Creativity Scale (PCS) on the designer's behavior [81]. The first phase was the collection of personality and PCS data, and the second phase was the collection of individual concept generation and selection data. During the first phase, the participants provided information about their personality and preferences for creativity by completing a short form of the five-factor model (FFM) personality test, more commonly known as the Mini-IPIP scale [83], and the PCS survey [80, 81]. One week after the completion of the PCS and the Mini-IPIP, an in-class session was conducted. The exact setup and procedure used during that study can be found in the paper by Toh and Miller [81]. Most relevant to the current study were the in-class sessions where students were given design goals and asked to generate concepts individually. The concept generation phase took 20 minutes, followed by the individual concept selection phase. During concept selection, participants were given a stack comprised of all of their team members' ideas that were not labeled by name and were asked to categorize each concept as *consider* or *do not consider* on a piece of paper, where concepts in the *consider* category were ideas that the participant felt were most likely satisfy the design goals and concepts in the *do not consider* category were those participants felt had little to no likelihood of satisfying the design goals. This indicator was also chosen as it also fits into the course curriculum, where the binary decision participants made toward *consider* vs *not consider* would help to determine whether an idea would be considered for the next phase of the project – prototyping. This was captured on a concept evaluation sheet. After data collection was completed with the participants, the ideas they generated were evaluated by two quasi-expert raters in terms of their quality and novelty. Details on the evaluation process can be found in the Metrics section below. Finally, the teams were simulated using Python, and the modified SDT categories were calculated for each idea selection event.

4.3 Team Simulation

Capturing team data is often difficult due to its time-consuming nature and population requirements. For example, the previous individual data collection by Toh and Miller [81] took three years to complete and resulted in the analysis of 75 students (around 19 teams). A power analysis of this data revealed that to reach a medium effect size (0.15) with 5 or 4 predictor variables, a minimum sample size of over 138 or 129 teams would be required, respectively. In order to overcome the challenges of capturing this large dataset simulated teams were used.

Specifically, for this paper we relied on the process used in a previous study by Alzayed et al. [125] to simulate design teams based on individual data. This approach was described in more detail in the paper by Peng, et al. [59]. The simulation model used in this study involved nominal brainstorming teams, where the ideas are first generated individually and then pooled together as a team [126–129].

This strategy has been used in previous studies where nominal problem-solving teams have been simulated and their results effectively analyzed [125, 130]. Using the data of 75 students, all possible combinations of four-person teams were simulated within each class section. For this study, Jupyter Notebook and Python were used for the simulation, with the following libraries: pandas and numpy. More specifically, the original dataset was used to extract key information such as the design task assigned to the participant, the course section and instructor of the participant, and their idea generation outputs. Participants were separated into smaller groups based on their course section and design task assigned. The total number of participants in each group was used to generate all combinations of groups of 4, See Table 1 for a summary of the different team combinations produced by the simulation. As a result of the simulation, a total of 52,976 teams were produced. This simulation method was to ensure that all possible combinations would be considered in the analysis and that each type of team could be found in the population [131]. After the participants were organized into their new groups, their individual attributes, such as each of the personality factors, were averaged to produce a team-level metric. Their design decisions were also collected and summed into a team value.

4.4 Metrics

This section highlights the metrics used in this study and their computations.

Mini-IPIP: The Mini-IPIP test is a shortened version of the IPIP-NEO (International Personality Item Pool Representation of the NEO PI-RTM), was developed to quantify the personality of an individual to see how they fit in a five-factor model [83]. This model includes a total of 20 questions, the answers of which were taken on a 5-point Likert scale that ranges from "Completely Disagree" (1) to "Completely Agree" (5). The questions were aggregated into five factors: Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness. However, it is important to note that in some literatures, the last term is labeled as Intellect/ Imagination [83, 84]. The scores of the five factors were calculated by taking the average of the questions under each factor.

Preference for Creativity (PCS): The Preference for Creativity Scale [132] was developed by Toh and Miller [107] as a tool for measuring the preference of individuals in the concept screening process to identify and understand the possible underlying factors that may play a role in the evolution of creative ideas. This scale is broken down into four factors: Team Centrality and Influence (TCI), Risk Tolerance (RT), Creative Confidence and Preference (CC), and Motivation (M). The responses to the questions follow a five-point Likert scale. The coefficient α for this scale was 0.70. The scores for each factor were calculated based on methods outlined by Toh [133].

Design Novelty: This metric assesses the originality and uniqueness of each idea produced and is an important contributor to engineering design creativity. For this study, design novelty was calculated for each generated idea using a Design Rating Survey (DRS) developed based on the feature tree approach by Shah et al. [134]. Details on this rating process can be found in the study by Toh and Miller [135]. More specifically, scores were given to each idea based on the DRS by quasi-expert raters. the raters were undergraduate Mechanical Engineering students who were trained extensively in the design tasks and the rating process. They attended training sessions and the survey used was explained to them in detail to ensure agreement between the raters. Design novelty was assessed according to the task given to the students and groups of questions within the DRS were dedicated specifically to different tasks. The final rating resulted in inter-rater reliability of over 0.75 for all design tasks. Disagreements between the raters were settled through discussion. The metric decreases the novelty score when the idea shares a lot of features with other generated ideas in that study, and increases the score when it has unique features in comparison with other ideas [81]. The DRS survey can be found at (http: // www.engr.psu.edu/britelab/resources. html). For this study, the median novelty of the entire population was used to separate the dataset into two categories: radically innovative and incrementally innovative, with those falling on the median being categorized a radically innovative as well.

Design Quality: For this study, the average quality of generated ideas and selected ideas were adapted from the study by Toh and Miller [81]. The quality of the idea is defined here as a measure of how technically feasible a design is [136]. It also is a measure of how well the design meets the specifications and criteria [134]. The metric and questionnaire used to evaluate the quality of ideas produced by the population studied here, as well as the equation used to calculate the design quality of an idea can be found in the study by Toh and Miller [136]. The survey used is a part of the DRS used for design novelty and therefore shares its inter-rater reliability score. At the end of the DRS, there were four questions that evaluated the technical feasibility of the idea. During this process, quasi-expert raters were asked to answer four questions regarding the generated concept. The raters were the same two undergraduate Mechanical Engineering students who rated the ideas for

Table 2. Signal detection table for radical innovation

		SELECTION	
		Select	$\overline{Select}$
IDEA QUALITY	Good	HIT: when a good (or high quality) and creative idea is selected for further development	TYPE I ERROR: when a creative and high-quality idea is neglected
	$\overline{Good}$	TYPE II ERROR: when a creative but low-quality idea is selected for further development	CORRECT REJECTION: when a creative but low-quality idea is correctly neglected

design novelty. For this study, the median quality of the entire population was used to separate the dataset into two categories: high-quality/good ideas and low-quality/bad ideas.

Signal Detection Theory for Radically Innovative Designs: For this study, the classification of radical innovation was done based on the Design Novelty Metric. More specifically, the median novelty score for the entire population was utilized to effectively split the data in half. The median novelty score for this population was 0.725. Therefore, ideas with high novelty, or a novelty score equal to or above 0.725, were considered radically innovative, and ideas with low novelty, or a novelty score below 0.725, were considered incrementally innovative (and were thus not discussed in this paper). This was based on the definition of novelty, which is a measure of how different an idea was from other ideas [134, 137, 138]. Once radically innovative ideas were identified, individual decisions were classified using Signal Detection Theory (SDT) as the basis. More specifically, the model used here was constructed based on the novelty of the ideas, the quality of the ideas, and whether the ideas are selected. Here, the quality cutoff used was the median quality of the entire population, which equaled 1. Therefore, any idea equal to 1 was considered high quality and good, while any idea below quality of 1 was considered low quality or bad. This can be better illustrated through Table 2, which includes the classifications of each signal.

Hit: The category of hit was a construct based on the Signal Detection Theory. It described a situation when a signal is perceived, and it was identified. Specifically for this study, a hit was used to describe an instance when the idea was rated as high in quality (signal observed), and it was selected for further development (observation noted).

Type I error: Type I error was a construct based on the Signal Detection Theory, where it described a situation when a signal is perceived, but it was not identified. Specifically for this study, Type I error was used to describe instances when the idea was rated as high in quality (signal observed), but it was not selected (observation not identified).

Type II error: Type II error was a construct based on the Signal Detection Theory as well, and it described a situation when a signal is not perceived, but an observation is made. Specifically for this study, Type II error was used to describe instances when the idea was rated as low in quality (signal not observed), but it was selected (observation identified).

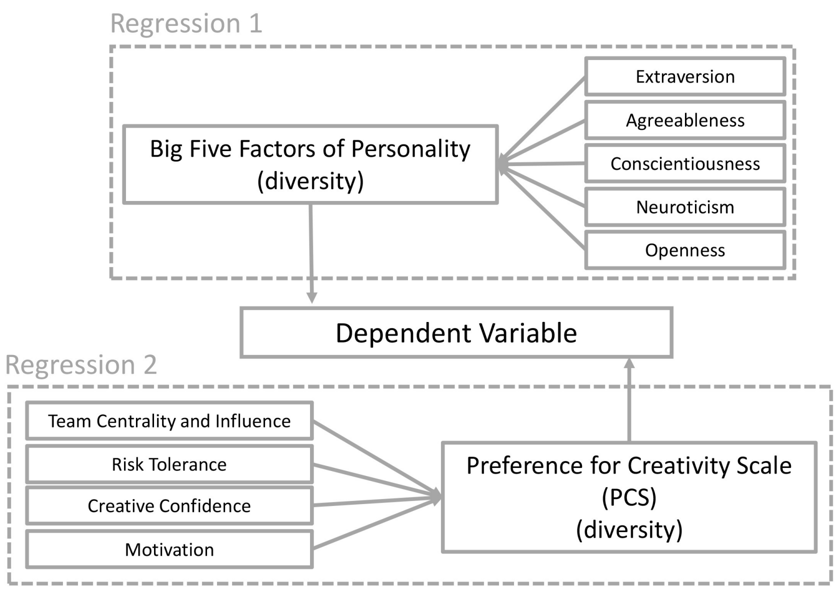

Fig. 1. Analysis structure for diversity of personality and preferences for creativity on effectiveness of team concept screening outputs.

Table 3. Average and standard deviation of personality and preferences attributes for the entire population

		Average	Standard Deviation
Personality	Extraversion	3.553	0.956
	Agreeableness	3.946	0.755
	Conscientiousness	3.497	0.714
	Neuroticism	2.495	0.721
	Openness	3.204	0.584
Preferences for Creativity (PCS)	Team Centrality and Influence	4.002	0.683
	Risk Tolerance	3.263	0.562
	Creative Confidence and Preferences	3.679	0.602
	Motivation	4.161	0.558

Table 4. Results of the eight multiple regression models were all significant

	Hit			Type I Error			Type II Error			Correct Rejection		
Diversity of Attributes	**B**	**Std. Coef. β**	**Sig**	**B**	**Std. Coef. β**	**Sig**	**B**	**Std. Coef. β**	**Sig**	**B**	**Std. Coef. β**	**Sig**
	$R^2 = 0.076$, $p < 0.001$			**$R^2 = 0.081$, $p < 0.001$**			**$R^2 = 0.099$, $p < 0.001$**			**$R^2 = 0.053$, $p < 0.001$**		
Extraversion	–0.473	–0.026	<0.001	2.060	0.173	<0.001	–0.957	–0.073	<0.001	*0.123*	*0.009*	*0.035*
Agreeableness	–4.305	–0.213	<0.001	–2.027	–0.151	<0.001	4.437	0.318	<0.001	2.932	0.192	<0.001
Conscientiousness	1.109	0.050	<0.001	*0.196*	*0.013*	*0.005*	–2.150	–0.133	<0.001	0.953	0.058	<0.001
Neuroticism	–4.171	–0.169	<0.001	2.390	0.146	<0.001	–1.335	–0.073	<0.001	1.946	0.105	<0.001
Openness	–0.478	–0.021	<0.001	1.450	0.098	<0.001	–1.135	–0.069	<0.001	–1.192	–0.071	<0.001
	$R^2 = 0.070$, $p < 0.001$			**$R^2 = 0.007$, $p < 0.001$**			**$R^2 = 0.052$, $p < 0.001$**			**$R^2 = 0.107$, $p < 0.001$**		
PCS: Team Centrality and Influence	–3.815	–0.190	<0.001	1.188	0.089	<0.001	*0.135*	*0.009*	*0.056*	1.193	0.079	<0.001
PCS: Risk Tolerance	–3.542	–0.145	<0.001	–0.601	–0.037	<0.001	–1.465	–0.081	<0.001	6.000	0.325	<0.001
PCS: Creative Confidence	5.451	0.212	<0.001	*–0.054*	*–0.003*	*0.539*	–3.440	–0.182	<0.001	–4.028	–0.208	<0.001
PCS: Motivation	5.567	0.164	<0.001	*–0.221*	*–0.010*	*0.033*	0.691	0.028	<0.001	–3.573	–0.140	<0.001

Note: gray and italicized entries indicate no significance.

Miss: The category of miss was a construct based on the Signal Detection Theory. It described a situation when a signal is not perceived, and it was not identified. Specifically for this study, a hit was used to describe an instance when the idea was rated as low in quality (signal not observed), and it was correctly not selected for further development (observation not identified).

5. Data Analysis and Results

The 52,976 simulated teams generated on average 96.652 ± 13.069 radically innovative ideas during the study. In order to identify the likelihood of an idea evaluation from these teams falling into the four categories SDT categories (i.e., "Hit", Type I error, Type II error, and "correct rejection"), standard multiple regression models were computed. For each research question, two regression models will be computed, one with the independent variables as the diversity of personality, and the other as the diversity of PCS, see Fig. 1. SPSS v. 29 was used to analyze the data collected. The average and standard deviation of the personality and preferences for creativity of this population can be found in Table 3. The significance level of the analyses was adjusted using Bonferroni adjustment to reduce statistical Type I errors made from multiple tests on the dependent variables. Since this paper explored the effects of nine independent variables, the new significance level was calculated as 0.05/9 which received $p < 0.006$. The results of each regression analysis can be found in Table 4. Effect sizes were determined by examining R^2 and categorized according to Cohen [139] and Bosco, et al. [140], where $R^2 < 0.01$ is a trivial effect, $R^2 = 0.01–0.09$ is a small effect, $R^2 = 0.09–0.25$ is a medium effect, and $R^2 > 0.25$ is a large effect. The remainder of this section highlights the findings with reference to the signal detection categories.

How team composition in terms of diversity of personality or Preferences for Creativity (PCS) factors influence:

5.1 RQ 1: The Likelihood of a Hit or Correct Selection Occurring in Radical Innovation Tasks

The aim of the first research question was to assess if team personality and preferences for creativity could be used to predict the likelihood of an evaluation falling into the Hit category for radical innovation in simulated teams. This research question was constructed to examine the simulated team's level of diversity in these attributes and their impact on the likelihood of an evaluation falling in the Hit category for radical innovation. Our hypothesis was that diverse teams in personality and PCS would be significantly related to a higher likelihood of Hit occurring.

The results of the first multiple regression analysis showed that the full model of the diversity of simulated team personality traits significantly predicted the likelihood of Hit occurring in radical innovation tasks, $R^2 = 0.076$, $F(5, 52970) = 866.022$, $p < 0.001$, a small effect size. All predictor variables added statistically significantly to the prediction, $p < 0.001$. On the other hand, the results of the second multiple regression analysis showed that the full model of the diversity of simulated team Preferences for Creativity (PCS) traits significantly predicted the likelihood of Hit occurring in radical innovation tasks, $R^2 = 0.070$, $F(4, 52971) = 992.514$, $p < 0.001$, a small effect size. All predictor variables added statistically significantly to the prediction, $p < 0.001$. Details of the results can be found in Table 4.

The model results indicated that there was a significant relationship between the model of personality and Hit occurrences, and between the model of PCS and Hit occurrences. However, the predictor variables were different from our hypothesis. Examination of the predictor variables showed that teams less diverse in Extraversion, Agreeableness, Neuroticism, and Openness and more diverse in Conscientiousness predicted higher Hit occurrences. In addition, less diverse teams in Team Centrality and Influence and Risk Tolerance, and more diverse teams in Creative Confidence and Preferences predicted higher Hit occurrences.

5.2 RQ 2: The Likelihood of Type I Error Occurring in Radical Innovation Tasks

The second research question was constructed to examine the impact of team composition of personality and preferences for creativity of the evaluator examined through their diversity on the likelihood of an evaluation falling in the Type I error category for radical innovation. Our hypothesis was that uniform teams in personality and PCS would be related to a higher likelihood of Type II error occurring.

The results of the first multiple regression analysis showed that the full model of the diversity of simulated team personality traits significantly predicted the likelihood of Type I occurring in radical innovation tasks, $R^2 = 0.081$, $F(5, 52970) = 936.301$, $p < 0.001$, a small effect size. All predictor variables added statistically significantly to the prediction, $p < 0.001$, except for Conscientiousness, $p = 0.005$. On the other hand, the results of the second multiple regression analysis showed that the full model of the diversity of simulated team Preferences for Creativity (PCS) traits significantly predicted the likelihood of hit occurring in radical innovation tasks, $R^2 = 0.007$, $F(4, 52971) = 98.949$, $p < 0.001$, a small effect size. All predictor variables added statistically significantly to the prediction, $p < 0.001$ except for Creative Confidence and Preference, $p = 0.539$ and Motivation, $p = 0.033$. Details of the results can be found in Table 4.

These results suggested that there is a significant relationship between the diversity of personality and the diversity of PCS on Type I error occurrences. An examination of the predictor variables indicated that teams more diverse in Extraversion, less diverse in Agreeableness, more diverse in Neuroticism, and more diverse in Openness were related to higher Type I error occurrences. On the other hand, teams more diverse in Team Centrality and less diverse in Risk Tolerance were related to higher Type I error occurrences.

5.3 RQ 3: Likelihood of Type II Error Occurring in Radical Innovation Tasks

This research question was constructed to examine the impact of team composition of personality and preferences for creativity of the evaluator examined through their diversity on the likelihood of an evaluation falling in the Type II error category for radical innovation. Our hypothesis was that uniform teams in personality and PCS would be related to a higher likelihood of Type II error occurring.

The results of the first multiple regression analysis showed that the full model of the diversity of simulated team personality traits significantly predicted the likelihood of Type II errors occurring in radical innovation tasks, $R^2 = 0.099$, $F(5, 52970) = 1165.67$, $p < 0.001$, a medium effect size. All predictor variables added statistically significantly to the prediction, $p < 0.001$. On the other hand, the results of the second multiple regression analysis showed that the full model of the diversity of simulated team Preferences for Creativity (PCS) traits significantly predicted the likelihood of Type II errors occurring in radical innovation tasks, $R^2 = 0.052$, $F(4, 54371) = 732.017$, $p < 0.001$, a small effect size. All predictor variables added statistically significantly to the prediction, $p < 0.001$ except for Team Centrality and Influence $p = 0.056$. Details of the results can be found in Table 4.

These results suggested that there was a significant relationship between the diversity of personality and the diversity of PCS and Type II error occurrences. Examining more specifically at the predictor variables, it was found teams less diverse in Extraversion, more diverse in Agreeableness, less diverse in Conscientiousness, less diverse in Neuroticism, and less diverse in Openness were related to higher Type II errors. In addition, teams less diverse in Risk Tolerance, less diverse in Creative Confidence and Preference, and more diverse in Motivation were related to higher Type II errors.

5.4 RQ 4: The Likelihood of Correct Rejection Occurring in Radical Innovation Tasks

This research question was constructed to examine the impact of team composition of personality and preferences for creativity of the evaluator examined through their diversity on the likelihood of an evaluation falling in the Correct Rejection category for radical innovation. Our hypothesis was that diverse teams in personality and PCS would be related to a higher likelihood of Correct Rejection occurring.

The results of the first multiple regression analysis showed that the full model of the diversity of simulated team personality traits significantly predicted the likelihood of Correct Rejections occurring in radical innovation tasks, $R^2 = 0.053$, $F(5, 52970) = 590.498$, $p < 0.001$, a small effect size. All predictor variables added statistically significantly to the prediction, $p < 0.001$ except for diversity of Extraversion, $p = 0.035$. On the other hand, the results of the second multiple regression analysis showed that the full model of the diversity of simulated team Preferences for Creativity (PCS) traits significantly predicted the likelihood of Correct Rejections occurring in radical innovation tasks, $R^2 = 0.107$, $F(4, 52971) = 1585.061$, $p < 0.001$, a medium effect size. All predictor variables added statistically significantly to the prediction, $p < 0.001$. Details of the results can be found in Table 4.

These results suggested that there was a significant relationship between diversity of personality and Correct Rejection occurrences, as well as between diversity of PCS and Correct Rejection occurrences. In terms of the predictor variables, the results here suggested that teams more diverse in Agreeableness, more diverse in Conscientiousness, more diverse in Neuroticism, and less diverse in Openness were related to a higher likelihood of correct rejections. In addition, teams more diverse in Team Centrality and Influence, more diverse in Risk Tolerance, less diverse in Creative Confidence and Preference, and less diverse in Motivation were related to a higher likelihood of Correct Rejection.

6. Discussion

This paper was designed to investigate the impact of personality and preferences for creativity at the team level on the team's concept screening performance. Table 5 provides a summary of these findings. Overall, the results show that the composition of less diversity versus more diversity of all attributes for higher Hit is 6 (less diverse in 6 attributes): 3 (more diverse in 3 attributes), for lower Type I error is 4: 3, for lower Type II error is 2: 6, and for higher Correct Rejection is 3:5. Indicating that overall, less diversity in the attributes might result in higher Hits, less diversity might result in lower Type I errors, more diversity might result in lower Type II errors, and more diversity might result in Correct Rejections. However, this is just a very rough summary of the results, and more details on what was found will be discussed in the following subsections.

1. No composition of attributes was found to have the best decision-making in terms of higher correct decisions (Hit and Correct Rejection) and lower errors (Type I and Type II).
2. Teams more diverse in Conscientiousness have the most benefits (higher Hit, lower Type II error, higher Correct Rejection) and the least setbacks (no relation to Type I error).

Table 5. Result summary for diversity of team attributes on types of decisions made where + indicates more diverse teams and – indicates less diverse teams

		Hit	Type I Error	Type II Error	Correct Rejection
Big 5 Factors of Personality	Extraversion	–	+	–	
	Agreeableness	–	–	+	+
	Conscientiousness	+		–	+
	Neuroticism	–	+	–	+
	Openness	–	+	–	–
Preference for Creativity Scale (PCS)	PCS: Team Centrality and Influence	–	+		+
	PCS: Risk Tolerance	–	–	–	+
	PCS: Creative Confidence and Preference	+		–	–
	PCS: Motivation	+		+	–

Note: + indicates direct relationship, – indicates inverse relationship, blank indicates no relationship.

3. Teams more diverse in Risk Tolerance and less diverse in Openness were found to achieve more benefits (3) than setbacks (1). This is also true for teams less diverse in Extraversion (2 benefits: 1 setback), Team Centrality and Influence (2:1), and Motivation (2:1) and more diverse in Creative Confidence and Preferences (2:1)
4. Teams less diverse in Agreeableness and Neuroticism were found to achieve an equal amount of benefit (2) versus setback (2).

6.1 Composition of Conscientiousness was found to have the Most Benefit for making Design Decisions

The first main finding of this paper was that teams more diverse in Conscientiousness were associated with a higher likelihood of correct decisions (Hit and Correct Rejection) and lower errors (Type II). It is also important to note that the remaining category, Type I error, was not significant in the model. This meant that here, teams that included members who were very different in whether they wanted to follow pre-determined plans and their focus on achievements made better decisions. This increase in diversity in Conscientiousness could result in a team composition that benefited from the diversity of opinions [20, 22–24] based on mixed levels of change preference. In addition, since Conscientiousness was found to be not related to Type I error, it could be hypothesized that of all compositions, more diverse Conscientiousness might be the composition that has the most benefits and least setbacks.

6.2 Team Composition of Openness, Risk Tolerance, Extraversion, Team Centrality and Influence, Motivation, and Creative Confidence and Preference can Result in more Benefits than Setbacks

For both Openness and Risk Tolerance, their composition achieved better decisions in three out of four categories. More specifically, it was also found that teams less diverse in Openness had a higher likelihood of picking a good and novel idea, not missing a good idea, and correctly rejecting an idea. However, it is important to note that teams less diverse in Openness were also related to higher occurrences of Type II error, or the selection of a bad idea. This could be because Openness is a measure of curiosity and experience [86] and uniformity in this trait might result in too much agreement with each other that they fail to see a bad idea. For Openness, the standard coefficient β value for the relationship with Type II error and Correct Rejection are similar (Type II error β = –1.135, Correct Rejection β = –1.192), indicating that given the same composition (higher or lower diversity), the increase in one will be approximately the same as the decrease in the other. Therefore, researchers and educators should carefully consider the desired output when using this information, since less diversity can achieve more optimal results in three categories (higher HIT, lower Type I error, and higher Correct Rejection) but can also result in worse results in Type II error.

In addition, more diverse teams in Risk Tolerance were found to result in fewer errors (Type I and Type II) and more correct decisions (Correct Rejection). This indicates that teams that differ more in their ambiguity and risk preference [111–115] can make better decisions in terms of less neglecting a good idea, less selecting a bad idea, and more rejecting a bad idea. However, it is important to note that higher diversity in Risk Tolerance can also lead to a lower likelihood of Hit occurring, or a decreased likelihood of selecting a good idea. A closer examination of the data indicated that the relationship between Risk Tolerance and Hit had a higher standard coefficient β value while the relationship between Risk Tolerance and Type I error had a lower β value. Since the β value is an indicator of the strength of each predictor variable, it can be inferred that Hit and Risk Tolerance had a stronger relationship than Type I error and Risk Tolerance. Therefore, the results could demonstrate that overall, increasing 1 unit of Risk Tolerance would result in around 3 less Hit compared to just around 0.6 less Type I errors. But it would also increase by around 6 Correct Rejections. This relationship is a demonstration of how complicated team-level interactions can be, and therefore also indicates a need for more closer examination of this specific factor.

Compositions of Extraversion, Team Centrality and Influence, Creative Confidence and Preference, and Motivation were able to achieve better decisions in two out of three categories, with the last category being not significantly related to the factor. More specifically, it was found that teams less diverse in Extraversion and Team Centrality and Influence were related to more Hit and fewer Type I errors. Diversity in Extraversion was found to be not related to Correct Rejection occurrences, and Team Centrality and Influence were not related to Type II error. This could indicate that teams that are less different in interpersonal engagement preferences [87] and socially outgoing tendencies [85-88], as well as creative tendencies [108], fear of rejection and failure [43], and sense of self and confidence [109] would select more good ideas and miss less good ideas. However, less diversity of Extraversion is also related to higher occurrences of Type I errors, or selection of a bad idea. This could indicate that this team composition results in teams selecting more ideas in general, regardless of idea goodness. On the other hand, less diversity of Team Centrality and Influence was related to lower occurrences of not selecting a bad idea. Since the results show that this composition is not related to the selection of bad ideas, we hypothesize that the relationship with Correct Rejection could be due to these teams selecting fewer ideas in general.

Creative Confidence and Preference composition were positively related to Hit and negatively related to Type II error, indicating that teams more diverse in creative preferences and confidence [81, 106] select more good ideas and less bad ideas. However, these teams also correctly reject less bad ideas. This indicates that when the diverse team is selecting ideas, they are making the correct decisions, however, when rejecting ideas, they make less correct decisions. Finally, for Motivation, it was found that less diverse teams were related to fewer Type II errors (selecting bad ideas) and more Correct Rejections, but also fewer Hits (selecting good ideas). This indicates that when teams are less diverse in terms of motivation to complete the task [81] and sensitivity to criticism [119], they tend to select fewer ideas, good or bad, but more correctly identify bad ideas to reject.

6.3 Composition of Agreeableness and Neuroticism were found to Result in the Same Amount of Benefits (2) versus Setbacks (2)

The third significant finding of this paper is that teams less diverse in Agreeableness and Neuroticism were found to only have two benefits versus two setbacks. More specifically, it was found that teams less diverse in Agreeableness were related to higher occurrences of Hit and fewer Type II errors, while teams less diverse in Neuroticism were related to more Hits and fewer Type I errors. This meant that teams less different in terms of their trust tendencies [85] and preference to conform [91] would have higher hits (selection of good ideas) but also higher misses (miss a good idea), lower false alarms (select a bad idea) but also lower correct rejection. When the group is selecting ideas, they tend to select good ideas versus bad ideas, however, they also show a high likelihood of not selecting good ideas. These complex results could indicate that the effects of Agreeableness can impact design decisions in convoluted ways, and therefore further investigation is needed to understand the details of its impact.

For Neuroticism, results indicate that teams less different in their emotional stability [94] would have more hits (selection of good ideas) and fewer misses (miss good ideas), but also higher false alarms (select bad ideas) and lower correct rejection of bad ideas. When examining groups based on this composition, it was found that they tend to select good and bad ideas. But when they are not selecting ideas, they also don't select good or bad ideas. This could be linked to prior work that found neuroticism to be linked to more reckless risk-taking [93].

7. Limitations and Future Works

However, although the current research goal was able to contribute to the understanding of team-level decision-making, limitations still exist. First, it is important to note that the population used here is limited in that the base population was gathered at one university. The teams used for analysis were also based on simulations. This limits the generalizability of the results gathered, as the population is limited, and the simulation may not represent the population as well as actual human participants. The results of this study were also theoretically based and are the first step towards a better understanding of team-based behavior in engineering academia.

Additionally, in terms of team composition, we only took into consideration the personality and preferences for creativity. Other team composition traits can also influence the team's performance, such as its gender composition. Therefore, future research can investigate the impact of other factors as well. In addition, the study is limited in that it only investigates the individual impacts of each factor. Future work should also be done on the interaction effect between personality and PCS factors since they overlap in some respects. This could have accounted for the change in the significance of individual attributes observed in the study and should be further investigated to determine if this hypothesis was true. In addition, the cutoff used for radical innovation and high-quality ideas was the median of the current dataset. Although this was an effective way of splitting the data into two categories, it also limited the generalizability of the findings to other populations that might have different cutoff points. Therefore, future investigations could examine more into this and see if the result holds for other cutoffs, or if an optimal cutoff exists for this type of study. In addition, our findings suggested that the same composition might be related to both higher likelihoods of correct decisions and errors. For example, a team more diverse in Conscientiousness had a higher likelihood of Type II and correct rejections. The exact reason behind this was not investigated here and could be an area for future examination.

In addition, the effect size, as assessed through the R^2, for these analyses was medium/low. This limits the generalizability of the results. Therefore, future research needs to investigate more deeply in this area to examine the reason behind the relatively low effect size. Repeating the analysis with a different population can also re-validate the results found here and offer more insight into the generalizability of the results.

8. Conclusion

The purpose of this research goal was to examine the diversity of team personality and preferences for creativity and their relationship with the probability of the idea-screening event falling into one of the four SDT categories (hit, Type I error, Type II error, correct rejection) that were modified for the creative design context. The results of the analysis showed that for the population studied here, compositions of personality and Preferences for Creativity evaluated through diversity demonstrated a complete relationship with the idea selection decisions of the teams. More specifically, teams less diverse in Extraversion, Agreeableness, Neuroticism, Openness, Team Centrality and Influence, and Motivation and more diverse in Conscientiousness, Risk Tolerance, and Creative Confidence and preferences could have a higher likelihood of making correct decisions. However, these relationships only extend to two or at most three categories of correct decisions (higher hit, lower Type I error, lower Type II error, and higher correct rejection). Therefore, while these teams had been found to perform relatively well during concept screening, they should be still used with caution. The results found in this research goal could help educators understand what to look for in their students and also support educators in determining the best team composition for the desired project outcome. It could also serve as empirical evidence supporting the role of team composition in student decision-making.

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