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Development of Student-Career Matching Algorithms from the SAT® Suite of Assessments

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Introduction

The College Board administers several standardized assessments that measure academic skills and knowledge—the SAT Suite of Assessments (College Board, 2017). Of these, perhaps the SAT® is best known, given its widespread use in college admissions. Other assessments in this suite include the Preliminary SAT/National Merit Scholarship Qualifying Test (PSAT/NMSQT®) (for 10th and 11th graders), PSAT™ 10 (for 10th graders), and the PSAT™ 8/9 (for 8th and 9th graders). These measures are proven, valid predictors of important indicators of academic performance, with SAT scores predicting college success (College Board, 2021) and PSAT-related assessment scores serving as indicators of college and career readiness (e.g., Proctor et al., 2010). Used together, PSAT 8/9 provides a baseline for a student's college and career readiness, the PSAT 10 and PSAT/NMSQT assess the progress a student has made, and the SAT provides information linking the student to colleges (College Board, 2017).

In addition to their focus on preparing students for college, high schools, and even middle schools have turned more attention toward helping students prepare for the workplace, with career exploration and career guidance seen as valuable endeavors. Relatedly, the College Board has provided career exploration resources for several years. Most recently, the College Board developed a free, comprehensive set of digital resources under BigFuture® that help all students explore careers, plan for college, and pay for college, and provide enhanced connections to data from the SAT Suite of Assessments. College Board previously had career tools, called Career Finder and Roadmap to Careers (RtC), in partnership with Roadtrip Nation®. Thus, past documentation references Roadmap to Careers and Career Finder rather than BigFuture.

The purpose of this report is to summarize the process that the Human Resources Research Organization (HumRRO) used to create the algorithms that allow BigFuture to identify matching occupations based on SAT Suite assessments. These algorithms are based on mappings we established between SAT Suite scores knowledge, skill, and ability (KSA) dimensions from the U.S. Department of Labor's Occupational Information Network (O*NET) content domain.

The process to develop these algorithms occurred across multiple projects, with an early emphasis on using the scores of PSAT-related Math, Reading, and Writing and Language tests (hereafter referred to as PSAT-related tests), and then later adaptations to allow for use of refined scoring for the entire SAT Suite of Assessments. In brief, that process included (a) Linking PSAT-Related Tests to O*NET KSAs, (b) Developing Algorithms for Matching Students to O*NET Occupations Based on PSAT-Related Test Scores, and (c) Adapting the Algorithms for Matching Students to O*NET Occupations Based on SAT Scores and Predicted SAT Scores. We discuss these phases in more detail below.

It is important to note that although the goal of the work in Phases 1 and 2 was to focus on using the PSAT-related scores, the effort is generalizable to the entire SAT Suite. The reason for this is that the scores for the SAT Suite are vertically aligned. The Skills Insight™ Report (College Board, 2017) that describes the meaning of scores at different ranges covers the entire suite.

Phase 1: Linkage of PSAT-Related Tests to O*NET KSAs

The first phase, carried out between May and July 2018, focused on mapping KSAs measured by the three PSAT-related tests (Math, Reading, Writing and Language) onto corresponding KSAs from the O*NET Content Model (e.g., Number Facility, Reading Comprehension). Our linkage process involved three steps:

- Step 1: Create Initial List of O*NET KSAs Potentially Related to the PSAT-Related Tests
- Step 2: Rate Strength of O*NET KSA – PSAT-Related Test Relations
- Step 3: Map PSAT-Related Score Levels onto O*NET KSA Level Ratings

In the following sections, we describe these steps and the information resulting from each one.

*Step 1: Create Initial List of O*NET KSAs Potentially Related to the PSAT-Related Tests*

The purpose of this step was to identify O*NET KSAs with the strongest potential relationship with students' scores on the PSAT-related tests. This initial list was created by two highly experienced, Ph.D.-level industrial-organizational (I-O) psychology subject matter experts (SMEs) (i.e., each with more than 15 years of applied experience, direct work with the O*NET framework, and assessment of individual difference constructs). First, the SMEs reviewed descriptions of what each PSAT-related test measures, sourced from the following URLs:

- https://collegereadiness.collegeboard.org/psat-8-9/inside-the-test/math
- https://collegereadiness.collegeboard.org/psat-8-9/inside-the-test/reading
- https://collegereadiness.collegeboard.org/psat-8-9/inside-the-test/writing-language

Second, the two SMEs reviewed descriptions of each O*NET KSA in the O*NET Content Model (available at: https://www.onetcenter.org/content.html). Third, each SME made *independent* judgments about the O*NET KSAs with the strongest relationship to scores on each PSAT-related test. At this point in the process, the SMEs erred on the side of inclusion when making these judgments, as the purpose here was simply to develop a broad preliminary list of O*NET KSAs that a subsequent group of SMEs would refine as part of Step 2. Fourth, the SMEs met to discuss the KSAs they had identified and came to complete consensus about the list of KSAs with the strongest potential relationship to PSAT-related tests.

*Step 2: Rate Strength of the Relationship between O*NET KSAs and each PSAT-Related Test*

For Step 2, we asked a new set of five SMEs to independently rate the strength of the relationship between each O*NET KSA and each PSAT-related test. Specifically, we asked these SMEs to rate how strongly they thought "students' standing on each KSA would relate to their scores" on each PSAT-related test. The SMEs who participated in this exercise were one master's-level and four Ph.D.-level industrial-organizational (I-O) psychologists who had direct experience with the O*NET Content Model and measurement of individual difference constructs.

Results of the Step 2 SME Exercise

For each PSAT-related test, there was a subset of O*NET KSAs that all five SMEs agreed had a strong relationship with the given PSAT-related test and that showed clear content domain overlap with the PSAT-related test in question. Following those subsets, there tended to be a subset of O*NET KSAs reflecting more general mental abilities that SMEs rated as having a relationship to the PSAT-Related subtests (e.g., deductive and inductive reasoning abilities). Unlike the first subset of O*NET KSAs, there was less clear content domain overlap between these KSAs and the PSAT-related test in question. SMEs still tended to rate them as having a relationship to PSAT-related test scores, recognizing that there is a "*g*" (i.e., general) factor that contributes to shared variance among such abilities and the PSAT-related tests. In light of these results, the project team decided to retain only those O*NET KSAs that SMEs all agreed had a strong relationship with the PSAT-related test in question and that had clear content domain overlap with the given test. This decision rule also helped ensure that the O*NET KSAs tied to each PSAT-related test were distinct and nonoverlapping, which facilitates more meaningful student-occupation profile matching.

*Step 3: Map PSAT-Related Test Score Levels onto O*NET KSA Level Ratings*

O*NET KSA data come from job incumbents, who rate each O*NET KSA on two metrics:

1. How **important** is the given KSA to the performance of their current job?
2. What **level** of the KSA is needed to perform their current job?

Importance ratings are made on a 5-point scale ranging from 1 (Not Important) to 5 (Extremely Important). Level ratings are made on a 7-point scale where three of the seven rating points are anchored by a behavior that exemplifies the given level of KSA to perform effectively.

For Step 3, we asked six SMEs[1] to independently determine the minimum score range on each PSAT-related test that would be necessary to execute the behavior described in each "level" anchor of each O*NET KSA to which it was linked in Step 2. Specifically, for each O*NET KSA level anchor, we asked SMEs to identity a given PSAT-related test's score range that reflected the minimum level of academic skills necessary to successfully execute the behavior described in the anchor.

Results of Step 3 SME Exercise

SMEs were largely in agreement with regard to the PSAT-related test score ranges reflecting the minimum level of academic skills needed to successfully execute the behavior described in each O*NET anchor. For example, for 26 of the 27 level rating anchors examined (96.3%), at least four of the six SMEs identified a common PSAT-related test score range. For seven of these anchors, all six SMEs identified a common test score range, and for seven other anchors, five out of six SMEs identified a common test score range.

For the 12 anchors on which four out six SMEs identified a common PSAT-related test score range, a group discussion was held among SMEs (and facilitated by the HumRRO project lead)

[1] Five of the six SMEs who participated in this exercise had previously participated in the Step 2 SME exercise. The new SME who participated in this exercise was also Ph.D.-level I-O psychologist who had direct experience with the O*NET Content Model and measurement of individual difference constructs.

to finalize the test score range to associate with that anchor. For each of these 12 anchors, the group came to a consensus decision to link the PSAT-related test score range that four out of the six SMEs had initially and independently identified as the corresponding PSAT-related test score range for those anchors.

There was one PSAT-related assessment – O*NET KSA anchor combination on which SMEs were evenly split in terms of what PSAT-related test score range to associate with the anchor (PSAT-related Writing and Language – O*NET Written Expression level rating 4 combination). Upon discussing this split with the participating SMEs, the two senior I-O psychologists who served as SMEs in Step 1 reviewed the PSAT-related Writing and Language score level descriptions and O*NET KSA anchor description and came to a consensus decision on the mapping for this combination.

These SMEs recommended mapping level ratings of 4 for O*NET Written Expression to the PSAT-related Writing and Language 20–24 score range. They agreed that a person scoring in the 25–29 range would likely be able to "write a *better* job recommendation" (i.e., the behavioral anchor in question) than a person who scored in the 20–24 range, but they felt that a person scoring in the 20–24 range could still *successfully* write a job recommendation.

Phase 2: Developing Algorithms for Matching Students to O*NET Occupations Based on PSAT-Related Test Scores

The work completed in Phase 1 provided a critical foundation for developing algorithms for matching students to O*NET occupations based on their PSAT-related scores. In the second phase of work, our focus shifted to formal development and evaluation of these algorithms. This work was conducted between November and December 2018.

The goal of Phase 2 was to develop a set of algorithms that use a student's PSAT-related scores and O*NET occupational data as input to provide various indices of student-occupation match. To help guide our development and evaluation work, HumRRO worked with the College Board to develop student use cases for College Board's BigFuture. The algorithms we developed were designed to support the following use cases:

- **Use Case 1: Providing PSAT-Related Fit-Related Feedback to a Student for a Given O*NET Occupation.** This use case assumes that a student viewing detailed information for an O*NET occupation in BigFuture will receive feedback with respect to their PSAT-related Math, Reading, and Writing and Language "skills fit" for that given occupation. To facilitate providing such feedback, for each occupation, the student's levels of Math, Reading, and Writing and Language skills fit will be classified into one of three fit categories:
    - **Cat 1:** Occupation is a "best bet" for the student with respect to ____ skills fit (where "___" is either Math, Reading, or Writing and Language).
    - **Cat 2:** Student likely has sufficient ____ skills to perform the occupation … but it's not among their "best bets."
    - **Cat 3:** Student likely needs to improve their ____ skills to perform the occupation.
- **Use Case 2: Providing Students with an Ordered List of O*NET Occupations Based on Overall PSAT-Related Assessments Skills Fit.** This use case assumes a

student wants to obtain a simple rank-ordered list of O*NET occupations with respect to their overall PSAT-related skills fit. This will require having an overall PSAT-related assessment skills fit score for each student-occupation combination. Each occupation in a student's rank-ordered list could also potentially be annotated with its standing on the Math, Reading, and Writing and Language categorical fit metrics as described under Use Case 1.

- **Use Case 3: Providing Students with an Ordered List of O*NET Occupations Based on a Specific Type of PSAT-Related Assessment Skills Fit.** This use case assumes a student wants to obtain a simple rank-ordered list of O*NET occupations with respect to a specific type of PSAT-related assessment skills fit: Math, Reading, or Writing and Language. Each student will have such fit scores for each occupation. Each occupation in a student's rank-ordered list could also be annotated with its standing on the Math, Reading, and Writing and Language categorical fit metrics described under Use Case 1.

In the sections that follow, we provide a high-level overview of the process we used to develop and evaluate student-occupation matching algorithms to support each of these uses' cases.

*Expressing O*NET Level Ratings on the PSAT-Related Test Score Metric*

The first step in developing student-occupation matching algorithms involved using the final mapping between O*NET level rating anchors and the PSAT-related test score metrics resulting from Phase 1's Step 3 SME exercise to develop equations for transforming O*NET KSA level ratings for O*NET occupations so they are expressed on the PSAT-related test score metrics. The goal was to create O*NET KSA rating composites expressed on the PSAT-related Math, PSAT-related Reading, and PSAT-related Writing and Language score metrics for each of the 967 O*NET occupations that have KSA data in the O*NET 23.0 Database.[2] These composites, along with students' PSAT-related scores, serve as the primary inputs to the student-occupation matching algorithms we developed for this effort. Given the sensitive nature of this information, we do not detail the process used to create these composites.

Specifying the Algorithms

At a high level, the algorithms HumRRO created involve

- comparing user PSAT-related test scores to O*NET KSA rating composites expressed on the PSAT-related Math, PSAT-related Reading, and PSAT-related Writing and Language test score metrics for each of the 967 O*NET occupations; and
- customizing that comparison to create user-occupation outputs for each of the three use cases described above.

Evaluating the Student-Occupation Matching Algorithms

To evaluate the algorithms underlying the student-occupation fit scores, we first simulated individual-level PSAT-related test scores for 10,000 students using data furnished by the

[2] At the time this work was conducted in late 2018, 23.0 was the latest available version of the O*NET Database. As of the writing of this report version 24.2 is the latest available version (see https://www.onetcenter.org/db_releases.html for links to the latest and archival versions of the O*NET Database).

College Board on the relative frequency of all possible PSAT-related assessment score combinations (Math, Reading, and Writing and Language) in the PSAT/NMSQT respondent population. With these simulated data in hand, we evaluated empirical characteristics of the student-occupation fit scores for potential anomalies and to better understand how they function among a large representative sample of simulated students.

Occupations and Fit Categories

We first examined how many O*NET occupations would fall into each fit category described under Use Case 1. The main purpose here was to confirm that most students would have around 50 occupations identified as "best bets" based on their PSAT/NMSQT scores.

On average, around 50 occupations were deemed "best bet" (Cat 1 occupations) based on the categorical Math, Reading, and Writing and Language fit metrics. This finding confirms the algorithms for calculating these categorical fit metrics work as intended in this respect. Relatively few occupations fell into the lowest fit category for students (Cat 3). This finding was most pronounced for Reading fit and least pronounced for Writing and Language fit. This finding was expected, given that O*NET occupation PSAT/NMSQT scores (across 967 O*NET occupations) tended to be notably lower than student PSAT/NMSQT scores (across 10,000 simulated students). Overall, these results suggest the categorical fit scores are functioning as anticipated – highlighting a relatively small percentage (~5%) of O*NET occupations for student users of BigFuture to further consider as potential best bet fits with respect to their PSAT-related Math, Reading, and Writing and Language test scores.

*O*NET and PSAT-Related Test Score Distributions Across Occupations and Students*

Next, we compared the distribution of O*NET and student PSAT/NMSQT scores across occupations and students, respectively. Following up on the analyses summarized above, the purpose here was to summarize PSAT-related occupational requirements and see how they compare to scores in a simulated student population. We found occupation-level PSAT-related scores tended to be much lower than student PSAT/NMSQT scores.

To more directly tie the first and second set of results together, we constructed scatterplots that show relations between student PSAT/NMSQT test scores and the number of O*NET occupations falling into each PSAT-related fit category. Given the difference between student and occupation PSAT-related score distributions noted above, we expected and found there to be far more O*NET occupations falling into fit categories 1 or 2 as students' PSAT/NMSQT scores increase, and far fewer occupations falling into fit category 3. Effectively, students with higher PSAT/NMSQT scores have sufficient skills for more occupations (fit category at 1 and 2) and potentially insufficient skills for fewer occupations (fit category 3).

Types of Occupations and Placement into Fit Categories

Next, we conducted analyses to better understand how the classification of O*NET occupations into fit categories varied depending on the type of occupation examined. Particular attention was given to the extent to which occupations fell into fit category 1, because those are the occupations most likely to be surfaced to students in BigFuture. Specifically, we examined average percentage of occupations (across students) falling within each PSAT-related fit category by O*NET job zone and O*NET career cluster.

One way O*NET classifies occupations is in terms of the level of preparation needed to do work in that occupation, where "preparation" may reflect a combination of education, related experience, and on-the-job training. O*NET codifies these different levels of preparation in terms of "Job Zones."[3] We found that occupations that require little/no to medium levels of preparation (Job Zones 1, 2, and 3) tend not to be Cat 1 "best bet" occupations. In earlier analyses, we found about 5% of occupations *in general* fell into Cat 1, so when evaluating the percentages of Cat 1 occupations by job zone, 5% is a useful reference point. When it comes to occupations that require extensive preparation (Job Zone 5), the percentage of Cat 1 occupations is clearly elevated relative to the 5% baseline, particularly for Reading- (23.8%) and Writing-and-Language- (11.4%) related fit. For occupations that require considerable preparation (Job Zone 4), the percentage of Cat 1 occupations is elevated for Math-related fit but close to the 5% baseline for Reading- and Writing-and-Language-related fit.

Another finding of note regards trends among Cat 3 occupations. Earlier analyses had indicated that the baseline occurrence for Cat 3 occupations was 10.7% for Math-related fit, 2.8% for Reading-related fit, and 34.1% for Writing-and-Language-related fit. In contrast, among occupations that require extensive presentation, these percentages were much higher; among occupations that require little to some preparation, these percentages were much lower. This finding indicates that occupations requiring (a) extensive preparation are likely to have higher PSAT-related skill requirements (and, in turn, a higher percentage of them may fall into Cat 3 relative to occupations in general), and (b) little to some preparation are likely to have lower PSAT-related skill requirements (and, in turn, a lower percentage of them may fall into Cat 3 relative to occupations in general).

O*NET also classifies occupations into the 16 career clusters from the National Career Clusters® framework (https://careertech.org/career-clusters). These career clusters are sets of occupations in the same field of work that require similar skills (see also: https://www.onetonline.org/find/career). We examined the average percentage of occupations in Cat 1 across the PSAT-related tests. As with the results by job zone, a useful point of comparison for evaluating the percentage of Cat 1 occupations by career cluster is the 5% baseline noted above.

We found that, relative to the 5% baseline, higher percentages of STEM and Finance occupations and lower percentages of Manufacturing, Law, and Arts occupations are Math Cat 1 occupations. This pattern of findings makes sense given the difference in math-related skill requirements for these types of occupations. A comparable pattern, albeit involving different career clusters, emerges with respect to Reading and Writing and Language Cat 1 occupations. Specifically, relative to the 5% baseline, higher percentages of STEM and Education & Training occupations and lower percentages of Manufacturing and Hospitality & Tourism occupations are Reading and Writing and Language Cat 1 occupations. Again, this pattern of findings makes sense given the difference in verbal-related skill requirements for these types of occupations.

Another finding of note regards trends among Cat 3 occupations. We found earlier that the baseline occurrence for Cat 3 occupations was 10.7% for Math-related fit, 2.8% for Reading-related fit, and 34.1% for Writing-and-Language-related fit. Among STEM occupations in particular, these percentages are much higher, and among types of occupations that tend to be less cognitively demanding (e.g., Manufacturing, Hospitality & Tourism), these percentages are

[3] For a complete specification of how O*NET defines Job Zones, see: https://www.onetonline.org/help/online/zones; to learn more about how the Job Zones were created, see Oswald et al. (1999).

much lower. Again, these are sensible results given that occupations with (a) higher cognitive demands will have higher PSAT-related skill requirements (and, in turn, a higher percentage of them may fall into Cat 3 relative to occupations in general), and (b) lower cognitive demands will have lower PSAT-related skill requirements (and, in turn, a lower percentage of them may fall into Cat 3 relative to occupations in general).

Closeness of Student-Occupation Matches

Although the results presented above help inform the allocation of occupations into fit categories, they do little to inform how close of a match Cat 1 occupations are for students. To examine this issue, we calculated the raw and absolute differences between student- and occupation-level Math, Reading, and Writing and Language PSAT-related scores across all student-occupation dyads within fit Category 1. For comparison, we also examined these differences among student-occupation dyads within fit categories 2 and 3, as well as all student-occupation dyads across fit categories. Raw differences were calculated as student PSAT/NMSQT score minus occupation-level PSAT-related mean score.

We found raw and absolute differences between student and occupation PSAT-related scores among student-occupation dyads in Cat 1 were substantially smaller than those differences among dyads in Cat 2 and across all student-occupation dyads. Remember, smaller differences here mean better fit. This was to be expected and signifies that occupations in Cat 1 provide relatively better matches for students with respect to the given skill examined.

Finally, as we did for the fit category results discussed above, we conducted analyses to better understand how the raw and absolute differences between occupation-level and student PSAT-related scores varied depending on the type of occupation examined. Results revealed that occupations that (a) require considerable (Job Zone 4) or extensive (Job Zone 5) levels of preparation tend to be better fits for students (on average) than occupations that require less preparation, and (b) generally have higher cognitive demands (e.g., STEM, IT, Finance) tend to be better fits for students (on average) than occupations that generally have lower cognitive demands (e.g., Manufacturing, Construction, Hospitality). These findings help reinforce the claim that the algorithm is functioning as intended, given the level differences observed between occupation-level PSAT-related scores and student PSAT/NMSQT scores presented at the outset of the algorithm evaluation section.

Phase 3: Adapting the Algorithms for Matching Students to O*NET Occupations Based on SAT Scores and Predicted SAT Scores

The threefold objective of this phase was to (a) update the algorithms to address changes in the O*NET database, (b) address changes in the SAT Suite level scores input into the algorithm, and (c) use SAT scores and predicted SAT scores as inputs. To conduct this phase, we engaged in three tasks:

- assess the impact of changes in the O*NET database
- evaluate the impact of SAT Suite score input changes, and
- update the algorithms.

We discuss our process in detail below.

*Assess the Impact of Changes in the O*NET Database*

The purpose of this task was to determine if and how changes in the O*NET database may affect the algorithms that we use. This is an important consideration, because O*NET is updated on a regular basis, and the algorithms rely heavily on O*NET data. The initial algorithms were developed using Version 23.0 of the O*NET database, and the latest version of the O*NET database (as of this writing) was Version 26.3.[4] So there were 14 releases between those two versions.

We started this task by reviewing the Historical Summary of Database Content Changes (National Center for O*NET Development, 2022) to identify all the updates made between Version 23.0 and Version 26.3. The changes included

- additions or updates to data provided for occupations,
- updates to occupation names or addition of names,
- updates to Level Scale Anchor descriptions for 89 anchors in the Abilities and Skills domains,
- minor updates to Content Model element names and descriptions,
- updates to 60 Level Scale Anchor descriptions for the Knowledge and Generalized Work Activities domains,
- updates to the O*NET-SOC 2019 occupational taxonomy structure based on the transition to the 2018 SOC, and
- identification of technology skills related to distance learning and remote training.

We determined that only one set of changes listed above could have any potential impact on the algorithms: “Updates to Level Scale Anchor descriptions for 89 anchors in the Abilities and Skills domains.”

[4] Version 27.0 was released on August 23, 2022.

To evaluate the potential impact of the anchor updates, we examined the specific anchor updates that were made by reviewing the report on the anchor updating process (Crawford et al., 2021). We determined that the anchor revisions would have no impact on the original SAT to O*NET mappings. The reasons for this are as follows:

- Only 20% of the relevant anchors were affected.
- In most cases, the anchor revisions were minor and simply amounted to updating the objects or activities referenced so that they were more in line with current technology or concepts encountered by the broader society.
- All relevant new or revised anchors were scaled to the same values by a panel of industrial-organizational psychologists, with each panel member making independent ratings of the scale values. Disagreements in the independent ratings were rare, and after a consensus discussion, all panelists agreed on the scaling of each anchor.

Thus, we determined that the changes to O*NET would have no impact on the utility of the algorithms when used with the updated O*NET database.

Evaluate the Impact of SAT Suite Score Input Changes

The purpose of this task was to determine whether the plans to change the algorithm input from SAT Suite Test-level scores to Section-level scores would affect the usefulness of the mappings and the algorithms. When the mappings and algorithms were developed, the algorithm was linked with SAT Suite scores at the "test" level for "Math," "Reading," and "Writing and Language." Given that the mappings were done with these three test scores separately, and not the section level scores, the concern was that this could have an impact on the usefulness of those mappings.

To determine whether this change would have a critical impact on the algorithms, we used the algorithms to calculate the predicted Reading test score for each O*NET occupation, and the predicted Writing test score for each O*NET occupation. Then, we calculated the correlation between these two metrics (.922). This demonstrated that there is essentially no information lost when combining the SAT Suite Reading and Writing section scores when they are applied to the O*NET occupations according to the mappings.

Thus, we determined that we would be able to use the mappings to update the algorithms with little to no impact on the usefulness of the results.

Update the Algorithms

Our next task was to update the algorithms so that they would function using Math and Evidence-Based Reading and Writing (ERW) SAT and predicted SAT section scores (e.g., predicted based on PSAT 8/9, PSAT 10, PSAT/NMSQT scores) as inputs.

To conduct this task, we used the mappings to inform algorithms that would calculate predicted ERW and Math section scores based on O*NET occupational data. We updated the algorithms using the standard error of measurement and score ranges for ERW and Math SAT, and predicted ERW and Math SAT scores.

The algorithms we created involve comparing user SAT or predicted SAT section scores to O*NET KSA rating composites expressed on the SAT Math and SAT ERW score metrics for each of the 923 O*NET occupations, and customizing that comparison to create user-occupation outputs for each of the three use cases presented earlier under “Phase 2: Developing Algorithms for Matching Students to O*NET Occupations Based on PSAT-Related Scores”:

- **Use Case 1: Providing SAT Fit-Related Feedback to a Student for a Given O*NET Occupation.** This use case assumes that a student viewing detailed information for an O*NET occupation in BigFuture will receive feedback with respect to their SAT Math and ERW “skills fit” for that given occupation. To facilitate providing such feedback, for each occupation, the student’s levels of skills fit will be categorized as (1) the Student has sufficient skills to perform the occupation and the occupation is a “best bet” for the student with respect to ____ skills fit (where “___” is either Math, or ERW), (2) a Student likely has sufficient ____ skills to perform the occupation … but the occupation is not among their “best bets”, or (3) the Student likely needs to improve their ____ skills to perform the occupation.
- **Use Case 2: Providing Students with an Ordered List of O*NET Occupations Based on Overall SAT Skills Fit.** This use case assumes a student wants to obtain a simple rank-ordered list of O*NET occupations with respect to their overall SAT skills fit. The algorithm will provide an overall SAT skills fit score for each student-occupation combination.
- **Use Case 3: Providing Students with an Ordered List of O*NET Occupations Based on a Specific Type of SAT Skills Fit.** This use case assumes a student wants to obtain a simple rank-ordered list of O*NET occupations with respect to a specific type of SAT skills fit: Math or ERW. Each student will have these types of fit scores for each occupation.

These algorithms will work effectively with BigFuture as they are designed to use both predicted SAT scores and actual SAT scores.

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