THE OCCUPATIONAL SKILLS AND KNOWLEDGE INVENTORY (OSKI): A MEASURE VALIDATION STUDY ASSESSING PERSON-OCCUPATION FIT

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ABSTRACT

With the changing nature of work, the strategic application of competencies such as skills and knowledge within the workforce is crucial to addressing the needs of the modern workplace. As such, governments, education institutions, and organizations are in consensus that there is a need for systematic assessments that measure these competencies. In line with these concerns, this study achieved two main goals. First, we adapted and validated a comprehensive skills and knowledge inventory that maps directly into O*NET skills and knowledge based on the Career One Stop *Skills Matcher* – a widely used skills inventory. Second, using three samples (including two longitudinal datasets), we provided validation evidence to support the measure's adherence to statistical properties by examining validity evidence (concurrent and predictive). We found that convergence between corresponding skills and knowledge ratings with current and ideal careers coincided with higher reports of career outcomes such as career-choice satisfaction and demands-abilities fit (perceived fit) due to person-occupation fit. Also, the Occupational Skills and Knowledge Inventory (OSKI) examined reliability evidence explicitly focusing on profile reliability and rank-order stability (test-retest). We found that across profiles and samples, scores remained relatively consistent. These results are useful in advancing practical applications of skills and knowledge career exploration tools, as individuals and organizations can use them for career guidance. Overall, our measure provided essential validity and reliability evidence supporting its psychometric properties, which was a previous disadvantage of pre-existing skills and knowledge career exploration tools.

*Keywords: skills, knowledge, O*NET, skills matcher, career, organizations*

TABLE OF CONTENTS

The Occupational Skills and Knowledge Inventory (OSKI): A Measure Validation Study Assessing Person-Occupation Fit

With the changing nature of work, the strategic application of competencies such as skills and knowledge within the workforce is crucial to addressing the needs of the modern workplace, as many jobs continuously require modifications of specialized skills and knowledge over time (LeFevre-Levy et al., 2023; Tschang & Almirall, 2021). Governments, organizations, and educational institutions have acknowledged the need for systematic assessments of skills and knowledge relevant to various occupations (Reedy et al., 2013; Williams, 2003; Wilson, 2013). Skills and knowledge contribute to innovation and play a critical role in determining person-environment fit, promoting effective job performance, and enhancing a firm's profitability (Kristof-Brown et al., 2005; Leiponen, 2005). Skills and knowledge assessments can offer social and economic benefits by helping to match people to jobs based on individual differences in competencies (Wilson, 2013). However, achieving these benefits requires the development of career exploration measures that link to occupational databases, such as the U.S. Department of Labor's Occupational Information Network (O*NET). The O*NET provides a comprehensive database that links relevant job descriptors to worker characteristics, including occupational knowledge, skills, and ability ratings (Peterson et al., 1999). By forming these linkages, skills, and knowledge, assessments can be derived that provide detailed information about how people's unique profiles of skills and knowledge are related to the job demands of different occupations.

Despite the availability of content-rich occupational data on the O*NET, few psychological assessments exist that map into O*NET's skills and knowledge domains. To our knowledge, only one publicly available online measure, Career One Stop's *Skills Matcher*, uses O*NET's skills and knowledge variables to provide career exploration information to individuals

(Burrus et al., 2013; National Research Council, 2010). In 2022 alone, the *Skills Matcher* page received 2.6 million views, indicating that the measure attracts a large audience. Yet, the *Skills Matcher* has no publicly available technical report documenting its measure development process and components of its relevant psychometric characteristics - e.g., reliability and validity evidence (U.S. Department of Labor Employment and Training Administration, 2023). Thus, without relevant technical reports supporting the measure's development, this approach limits the transparency of the measure, making it more difficult for researchers and practitioners to understand how the measure works and improve on it in future developments. Other types of pre-existing skills assessments explore narrower domains of skills, such as social, emotional, and behavioral (SEB) skills (Demaray et al., 2021; Knight et al., 2002; Soto et al., 2021a; Soto et al., 2022). These narrower assessments provide valuable data, but because they are not directly linked to O*NET occupational variables, they have limited applications for career exploration and organizational placement.

Thus, the current study advances research in two main ways. First, we adapted an integrative skills and knowledge assessment based on the Career One Stop *Skills Matcher* — called the Occupational Skills and Knowledge Inventory (OSKI) —using single-item scales that map into a wide range of O*NET variables that differentiate occupations based on their knowledge, skills, and abilities (KSA) demands using large and unique samples across three separate datasets. These single-item scales will facilitate scale development in the future as this study provides a selection of relevant items that can contribute to a large item pool (Maples-Keller et al., 2019). The three datasets included one nationally representative sample of U.S adults (Study 1) and two longitudinal datasets of unique participants transitioning into the workforce after graduation from a 4-year university and a community college. Thus, this article provides detailed, publicly available documentation of the scale development process, and it also assesses respondents' fit with careers based on their item-level responses.

Second, this article provides extensive validity and reliability evidence to support the measure’s utility for several different purposes, including but not limited to practical implications (American Psychological Association, 2014). In particular, we assessed convergent and criterion-related validity to evaluate the degree of person-occupation fit based on individual skills and knowledge self-ratings with their current and ideal career. Moreover, to collect reliability evidence, we focused on profile and rank-order stability to examine whether our measure provides consistent results within persons and over time. This evidence offers a series of positive implications associated with our measure. For example, in career guidance settings, we anticipate that the OSKI can help individuals understand how their current skills and knowledge relate to different occupations and identify areas for growth. Also, organizations can use the OSKI for employee placement and development, such as by helping guide reskilling and upskilling efforts to match employees to job openings within organizations better. Furthermore, such evidence will influence perceptions regarding the OSKI’s overall generalizability (via its ability to provide consistent intra-person results across distinct sample populations) and facilitate future replicability of the measure. As a result, this study’s overall goal was to adapt a validated measure with publicly available records of its development that can create a skills and knowledge profile based on item-level responses that match individuals directly to O*NET occupations.

Conceptualizing Person-Occupation Fit Using Skills and Knowledge

Generally, *skills* define a person’s capabilities, whereas *knowledge* relates to facts a person knows (Sackett et al., 2017). A variety of research fields study skills—including business, psychology, education, and economics—and each field employs different terminologies and taxonomies (Heijke & Ramaekers, 1998; Soto et al., 2021; Thiel & Thomsen, 2013). These taxonomies are divided into smaller subsets, often breaking apart ‘soft skills’ (e.g., social, emotional, and behavioral skills) and ‘hard skills’ (e.g., technical knowledge and aptitudes; Gutman & Schoon, 2013; Hendarman &Tjakraatmadja, 2012). Ability constructs, such as cognitive ability and physical ability, are closely related to skills and knowledge and are often studied together (Bastian et al., 2005; Ryan et al., 1996; Tach & Farkas, 2006). *Abilities* refer to relatively enduring attributes that reflect individuals’ capabilities for performing various tasks (Peterson et al., 1999). Skills, knowledge, and abilities provide useful information about people’s competencies, which can be linked to the demands of different occupations to give information on person-environment (P-E) fit.

Prior literature shows that skills, knowledge, and abilities can promote and predict a wide array of job-related outcomes (Ali et al., 2012; Dong & Howard, 2006; Kautz, 2014). However, there is a lack of research on using skills and knowledge inventories to assess person-environment fit. P-E fit refers broadly to the congruence between an individual and work environment and is concerned with the overlap between their characteristics. Under the umbrella of P-E fit, several types of fit exist, such as person-organization fit, person-vocation fit, and person-job fit (Kristof-Brown et al., 2005). This paper focuses on person-occupation fit, an aspect of person-vocation fit that addresses the congruence between a person’s attributes and those of their occupation. Person-occupation fit can further be divided into demands-abilities (D-A) and needs-supply (N-S) fit. While demands-abilities fit assesses the relationship between an employee’s skills, knowledge, abilities, and job demands (which is most relevant to the goal of our measure), needs-supply fit focuses on whether an employee's occupation meets their values, desires, or preferences (Edwards, 1991; Kristof-Brown et al., 2005).).

Mapping Occupational Knowledge and Skills into the O*NET

The Occupational Information Network (O*NET) is a database adapted and maintained by the U.S. Department of Labor consisting of occupation-related data from over 1,100 occupations. O*NET's fundamental organizing framework is a taxonomy of occupation-related data called the *O*NET content model* (Tippins & Hilton, 2010). The O*NET content model offers a framework that identifies the most critical types of occupational data concerning the job and organizational research and principles, with 277 descriptors collected by O*NET programs. This model was adapted to tackle three needs, which include: (a) the ability to describe occupations in several ways, (b) a common language of descriptors that are applicable across all occupations, unlike its predecessor – the Dictionary of Occupational Titles (DOT) (c) taxonomic classification system (Peterson et al., 2001).

O*NET collects information from a combination of sources, including job incumbents, occupational experts, and occupational analysts, to develop knowledge, skills, and abilities ratings (Reeder et al., 2020). Considering the current study's primary focus, which involves identifying crucial, trainable worker competencies, our use of O*NET is closely tied to knowledge, skills, and ability domains (Reeder et al., 2020). O*NET's database has over 120 skills, knowledge, and abilities constructed from more than 100 occupations for which ratings are collected over 21 cycles (Reeder et al., 2020). The inclusion criterion administered by O*NET relies heavily on interrater agreement and interrater reliability (Reeder et al., 2020). Given that our skills and knowledge assessment is an adapted version of the Career One Stop *Skills Matcher*, we next discuss the components of the original measure.

Career One Stop Skills Matcher

The Career One Stop *Skills Matcher* is a 40-item skills inventory developed by the U.S. Department of Labor Employment and Training Administration. The measure consists of a series of questions assessing respondents' level of skills and knowledge attributes in several areas, such as Chemistry, Quality Control, and Biology, under the broad construct of "skills" (U.S Department of Labor Employment and Training Administration, 2023). Each item is divided into five (5) skill levels (ranging from Beginner, Basic, Skilled, Advanced, Expert) that include prompt questions and behavioral anchors for what constitutes a beginner, skilled individual, or expert within each skill area. For example, for the item Administration and Management – participants are prompted with the following question: "How much do you know about business planning and leadership?". The behavioral anchor for the Beginner category for this item is "Complete a timesheet". In the Skilled category the anchor is "Monitor project progress to complete it on time,", and in Expert category, "Manage a $10m company".

Based on all self-reported skill and knowledge responses, a profile is generated that matches individuals to careers (U.S Department of Labor Employment and Training Administration, 2023). Although there is no publicly available information about how the person-occupation matching is done, this is typically done using profile correlations, as in the O*NET Interest Profiler (Rounds et al., 2021). Despite this, millions of individuals use the Skills Matcher (U.S Department of Labor Employment and Training Administration, 2023). The lack of publicly available documentation on its development and validation poses a challenge for researchers seeking to study the measure and justify its use in career and educational applications. As such, we next discuss the relevant considerations for adapting and validating our measure designed for use with O*NET's skills, knowledge, and ability domains, which borrows from Career One Stop's content and general measurement approach.

Development of the Occupational Skills and Knowledge Inventory (OSKI)

The overall goal of this study is to adapt a measure, termed the Occupational Skills and Knowledge Inventory (OSKI), which can be used to assess fit with O*NET occupations. Using three datasets, we tested the extent to which the OSKI is a reliable and valid tool for predicting career outcomes and can guide career decision-making across academic and work settings. To evaluate our measure, we next review the relevant aspects of content coverage.

Content Coverage

O*NET Occupational Knowledge. Knowledge (sometimes called hard skills) refers to one's level of expertise in different fields (Bell,1973; Blackler, 1995; Henderman & Tjakraatmadja, 2012). Within the O*NET content model, knowledge is one of the three areas that fall under worker requirements; there are 32 items within the knowledge domain (National Center for O*NET Development, 2023). The O*NET knowledge categories are organized and mapped onto occupational data based on their relative level and importance for each occupation coded within the O*NET's occupational database. In the current study, occupational knowledge ratings are a vital component in the adapted scale as they can provide insights necessary to explore an individual's knowledge fit with their current and ideal careers. Individual differences in knowledge have been shown to play a role in innovativeness, which is a crucial asset as the modern workplace evolves (Hendarman & Cantner, 2018; LeFevre-Levy et al., 2023; Tschang & Almirall, 2021). Furthermore, this construct can assist in determining specifically person-job fit (PJ fit) in terms of knowledge demands in the workplace (Carless, 2005). Examples of O*NET knowledge domains include Medicine and Dentistry, Psychology, and Transportation (National Center for O*NET Development, 2021; Peterson et al., 2001).

O*NET Occupational Skills. The O*NET's skills taxonomy is broken into two (2) higher-order constructs, seven (7) mid-level constructs, and 46 lower-level constructs (Peterson et al., 2001). These higher-order constructs are referred to as basic and cross-functional skills according to the O*NET (Peterson et al., 2001). *Basic skills* account for capacities essential for facilitating learning or acquiring knowledge and are further divided into content and process skills, which are among the mid-level constructs (Burrus et al., 2013; Peterson et al., 2001). *Content skills* relate to those specific skills which are acquired in various domains. Examples of content skills are tasks such as reading (Beck & Carpenter, 1986) and mathematics (Greeno & Simon, 1988). On the other hand, *Process skills* describe how individuals interact with information attained to facilitate learning, contributing to the rapid acquisition of knowledge and skills. Examples of process skills include active learning (Chi et al., 1989) and critical thinking (Halpern, 1994). The second construct - *Cross-functional skills* accounts for those skills that can apply to enhanced performance across various job contexts. Within the O*NET, these include mid-level constructs such as problem-solving skills and resource management skills (Fleishman et al., 1999; Peterson et al., 2001; Runco, 1994). Examples of O*NET skills domains include Science, Physical Strength, and Persuasion (National Center for O*NET Development, 2021).

In addition to knowledge and skills, cognitive and physical abilities have long been studied to predict career outcomes (Lavoie et al., 2017; Kaufman et al., 1987; Ritchie et al., 2015). Cognitive ability strongly predicts educational attainment, job performance, and health outcomes (Newman & Newman, 2020, pp.41-75). Physical abilities, such as psychomotor ability, also provide insight into the importance of physical attributes for performing certain types of jobs, especially those involving manual labor (Hadden et al., 2004; Hunter and Hunter, 1984). Granted the nature of our measure, we attempt to incorporate a few physical abilities under the skills domain, similar to how the O*NET conceptualizes them. Examples of relevant ability variables used in the current study are Body Coordination and Finger Dexterity (National Center for O*NET Development, 2021; Peterson et al.,2001).

Assessing Validity and Reliability

Convergent and Discriminant Validity Evidence

Validity evidence generally indicates that scores derived from a measure adequately represent the construct and provide a basis by which score interpretations can be used in decision-making processes (Hickman et al., 2021; Messick, 1989). *Convergent validity* investigates the relationship between measures of the same construct to identify how closely the different assessments are to each other (Crocker & Algina, 1986). This source of validity is achieved when correlations between measures of similar constructs using varying methods are significantly different from zero (Hinkin, 1998).

Based on our study's goal to adapt a measure that maps directly onto O*NET occupational variables, we assessed convergent validity by comparing individual self-reports of skills and knowledge with corresponding occupational variables from O*NET based on participants' current and ideal careers. To achieve this, we calculated convergence indices by computing a correlation between person-level reports of each skill and knowledge item and each specific O*NET occupational variable. For example, given that people are expected to self-select into careers based on their knowledge and skills, we expect to find positive relations between self-reported knowledge and the knowledge demands of their occupation. Although our study's approach to testing convergent validity differs from the traditional method, this approach aligns with our goals and accounts for the paucity of relevant occupational skills and knowledge inventory literature.

Additionally, to address discriminant validity within the present study, we assessed the relationships between specific knowledge and skills and how corresponding occupational variables correlate with occupations with non-corresponding occupational variables compared to those reported for current and ideal occupations. In this case, a discriminant index is estimated by subtracting the average of all non-corresponding skills or knowledge domains from the respective domain's convergence index, as done in previous measure development studies (Hickman et al., 2022). This index is useful as we expect that if someone scores high on a particular knowledge domain for example, medicine – we would expect a high discriminant index with an occupation variable such as artist, which does not require this specific knowledge domain. A low discriminant index would indicate that our measure is not discriminating well between occupational variables. Thus, the current study addresses discriminant validity by evaluating whether the OSKI shows patterns of discriminant relations with non-matching O*NET occupational variables.

Criterion-Related Validity Evidence

Criterion-related validity involves whether a measure adequately predicts a relevant outcome variable (Cronbach & Meehl, 1955). Even when career decisions are made based on individual perceptions of alignment of their skills and knowledge with specific careers – a perfect fit is not always achieved. As a result, we expect to find between-person variability in person-occupation skills and knowledge fit and for this variability to correlate with subjective career outcomes. In other words, according to our objective fit measure, people who show a better fit with their current occupation should report higher levels of job and career choice satisfaction and perceive higher levels of fit. These findings are critical for supporting the measure's usefulness in applied contexts, where it would likely assist individuals via the provision of career guidance and the acceptance of jobs in which individuals may be more satisfied.

Given that the OSKI is focused on knowledge and skill fit, we expect high correlations with perceptions of demands-abilities fit (D-A). To reiterate, D-A fit can be defined as congruence between an employee's knowledge, skills, and abilities with their job requirements (Edwards, 1991). Thus, in order to effectively measure criterion-related validity in the current study, we calculate profile correlations to assess fit and test whether better fit is associated with higher subjective career success. We evaluated this career success using profile correlations with perceptions of person-organization fit and career choice satisfaction, which have been said to be determinants of career success (Bretz & Judge, 1992; Brown, 2002; Guo et al., 2021; Haines et al., 2014; Judge, 1994; O'Neil et al., 2004).

Reliability Evidence

The current study focused on measuring two types of test-retest reliability: profile reliability and rank-order stability. *Profile reliability* reflects consistency in within-person rankings of skills and knowledge over time. Profile reliability is vital for our measure because within-person profiles of skills and knowledge are linked to O*NET occupations. A lack of profile reliability indicates that ordinal relations within an individual's scores are unstable or uncertain (Yarnold, 1984). This type of reliability was assessed by comparing skills and knowledge profiles across waves.

Rank-order stability assesses "the degree to which the relative ordering of individuals on a given variable is consistent over time." Unlike profile reliability, rank-order stability focuses on one variable at a time. It is typically indexed by correlations between scores on a variable measured over two time points (Baxter, 2005). We measured this type of reliability by examining test-retest reliability for each facet of the skills and knowledge domain. In combination with the validity evidence, the rank-order stability and profile reliability scores can provide evidence to support the applied use of our adapted measure.

Overview of Present Research

The purpose of the current paper is to adapt and validate a short, public-domain integrative measure based on the Career One Stop *Skills Matcher* (OSKI), which links directly to knowledge, skills, and abilities descriptors to O*NET's occupational-related data using single-item scales. The purpose of using the O*NET KSA framework was to organize knowledge, skills, and abilities hierarchically. We first selected basic knowledge, skills, and abilities central to the KSA literature to develop the measure and identify their respective O*NET KSA dimensions. Then, an initial pool of 51 items was generated to measure individuals' occupational knowledge (28) and occupational skills (23) in Study 1 using a diverse, nationally representative sample drawn from Prolific. This step was incorporated to improve the OSKI's structural validity, and assess its convergent, discriminant, and criterion-related validity. A refined pool of 46 items, including knowledge (27) and skills (19), were derived. To further examine the reliability and validity of the OSKI, we conducted two longitudinal studies that followed a unique group of recent graduates from 4-year universities (Study 2) and community colleges (Study 3). Together with these longitudinal samples, we further examined the reliability and validity of the OSKI along with its predictive power for career outcomes across 6- and 8-month periods during the transition from school to the workplace. Tables S2, S4-S5 in the supplementary materials provide demographic information on each of the samples in Studies 1-3.

Transparency and Openness

Data for all studies in this research is not publicly available, but we provide detailed reports on all samples, measures, and data in the following sections. Analyses were conducted using R (R Core Team, 2020).

Study 1: Item Generation, Scale Development, and Cross-Sectional Validity Evidence

Two significant goals influenced the adaptation of the OSKI. The first goal was identifying pre-existing skills and knowledge scales that mapped into O*NET's occupational variables. This goal guided our item generation process as we aimed to adapt an integrative scale unlike pre-existing narrower skills inventories (Soto et al., 2021) and determine whether our measure was the first of its kind. As previously discussed, to our knowledge, only one integrative skills inventory maps onto O*NET occupational data – The *Skills Matcher* – which organizes and measures skills and knowledge as a single construct (U.S Department of Labor Employment and Training Administration, 2023). As such, we used this measure as a starting point in conjunction with O*NET skills, knowledge, and abilities variables to develop our initial item pool. From these, we selected all of the occupational skills, knowledge, and abilities that were deemed suitable for self-reporting, removing duplicates as the O*NET classified some skills, such as Programming, in both the skills and knowledge categories.

A second major goal was selecting occupational skills, knowledge, and abilities items that mapped onto the O*NET occupational database. Ultimately, we strived to choose things that would be specific and most relevant to particular occupations, eliminating relevant items across all occupations. Furthermore, this method assisted in achieving our ultimate goal of matching people to careers based on their self-report ratings of their skills, knowledge, abilities, and current and ideal occupations. Previous research has incorporated this method via single-item scales connecting to constructs such as personality profiles (Maples-Keller, 2019). Similarly, we used this method to generate individual career profiles from item-level responses. From the *Skills Matcher,* we borrowed 33 items and added 13 new items, such as Transportation, Law, and Government, which can be linked to specific O*NET occupations, e.g., Lawyer. This process resulted in a refined item pool of 46 items, which was consistent with our larger goal of adapting an integrative measure that also maps directly onto O*NET occupational data. A panel of three industrial-organizational psychologists and three graduate students collectively selected or adapted the 46 items for the initial validation study.

Study 1 Participants

Sample 1 was drawn from an online data collection panel, Prolific, and contained 790 participants, representative of the U.S. population in terms of age, ethnicity, and gender. After data collection, cases were removed for participants who failed quality control questions; the final sample comprised 768 participants. Of the total sample, 383 participants accounted for 49.9% were female, 50.1% were male, and the average participant age was 45.8 years old (*SD* = 16.1). Upon completion, each participant was rewarded a $10 Amazon gift card. Table S2 in the supplement materials reports demographic information and characteristics of sample 1 participants.

Measures

Occupational Knowledge and Skills Inventory (OSKI). Participants were assessed using the 46-item OSKI – a newly adapted scale with items obtained from the Career One *Skills Matcher*. Given that the ultimate goal was to adapt an integrative skills, knowledge, and abilities scale map into O*NET's occupational information. Additional items were also obtained from the

O*NET knowledge and skills domain variables. These steps outline a key aspect of the item generation process. We adapted 33 out of 40 items from the Skills Matcher in our new measure.

In some cases, item titles were reworded or changed to reduce ambiguity due to the removal of behavioral anchors similar to that used in the *Skills Matcher* (U.S Department of Labor, Employment & Training Administration, 2023). Thus, 13 new items were included. Of the final 46 items in the OSKI, 27 knowledge items and 19 skills items were within the measure. The main exclusion criteria for the scale were based on duplicates in items such as Programming, which O*NET incorporates some items as both a component of knowledge and skills. As previously mentioned, the final scale contained 46 items. (See Table 1, p.30).

Items were reduced and generated based on the guidelines provided in previous measure development and validation research (Hinkin, 1998). During the reduction process, the study's authors also decided to omit some ability items, such as sustained attention, which have been deemed as unreliably measured via self-reports in past research (DeNisi & Shaw, 1977; Mabe & West, 1982; Peterson, 2001). The measure began with the prompt, "These statements are designed to gain information on your perceptions of your level of skills, knowledge, and abilities." It also included a single prompt for each category, such as "How much do you know about?" for knowledge items and "How skilled are you at?" for skills and ability items. Additional prompts included questions related to the participant's current and ideal occupation, which are discussed in the analysis strategy section. Participants were prompted to respond to each item using a 5-point Likert-type scale, ranging from 1 = *Beginner*, 2 = *Basic*, 3 = *Skilled*, 4 = *Advanced*, 5 = *Expert*. This method was chosen to reduce the potential ceiling effect, which may be present due to individual tendency to exhibit social desirability while completing the assessment (Podsakoff et al., 2003).

Outcome Measures

Career choice satisfaction. (α = .92). Five items were adapted from the Academic Major Satisfaction Scale by Nauta (2007) and used to measure individual satisfaction with the current career. A sample item is “Overall, I am happy with the career I have chosen.”

Fit Perceptions. Nine items from Cable and DeRue (2002) were used to assess three different types of fit perceptions: person-organization fit, needs-supplies fit, and demands-abilities fit. A sample item for person-organization fit (α = .95) is “My personal values match my organization’s values and culture.” A sample item for needs-supplies fit (α = .92) is “The job that I currently hold gives me just about everything that I want from a job.” A sample item for demands-abilities fit (α = .93) is “My abilities and training are a good fit with the requirements of my job.”

Analytic Strategy

One of the main goals of this validation study was to examine the psychometric properties of the newly adapted scale. As such, data was recorded in several Excel spreadsheets, and analysis was conducted using the software package R to gain initial insight related to the sample’s descriptive statistics, such as the mean and the SD, as well as the skewness of the sample distribution. Of the three studies, Participants in studies 2 and 3 were followed for several waves across six (6) months and eight (8) months, respectively, due to guidelines discussed for measuring outcomes in repeated measure designs and longitudinal studies (Ployhart & Ward, 2011). All participants were tested using the OSKI scale. However, observations across all samples were assessed for quality control and removed based on criteria such as “too little time spent taking questionnaire” as well as incomplete questionnaires, which can indicate occasional carelessness and random responses (Buechley & Ball, 1952; Huang et al., 2012; Richman et al., 1999; Schmitt & Stults, 1985). Another exclusion criterion used was based on the questionnaire's response patterns and it assessed in determining which items may not have been suitable for self-reporting, such as sustained attention (Arnicane et al., 2021; Mabe & West, 1982). Next, we discuss the strategy applied in the coding and assessment process.

Occupation Assessment and Coding. Participants' written responses regarding their current and ideal occupations were categorized based on O*NET occupations to merge occupational and participant data. This task involved participants responding to the questions: "What is your current occupation?" and "What is your ideal occupation?". After participants successfully reported their current occupations and their ideal occupations, the data was coded into O*NET occupations. Job titles were recorded independently by two research assistants, and all disagreements were resolved through discussion with the 1st author (a Ph.D. student in Industrial/Organizational Psychology), the third author (a Ph.D. student in Counseling Psychology), and the 4th author (an assistant professor in Industrial/Organizational Psychology). Lastly, O*NET occupational ratings for skills, knowledge, and abilities were integrated along with the coded occupations.

To assess convergent relations, we calculated correlations between participants' occupational knowledge and skill ratings and the corresponding occupational ratings from O*NET for both the current and ideal occupation. For the discriminant relations, we subtracted the average correlations between participants' ratings for non-corresponding skills from corresponding skills. The resulting discriminant index reflected the difference between converging skills and non-converging skills. This method follows a similar analysis conducted in past research, which assesses these aspects of validity of a research instrument (Hickman et al., 2022). Furthermore, composite scores were calculated for self-reported skills ratings, demands-abilities fit, needs-supplies fit, and career choice satisfaction to assign equal weights to each of the items included for each construct and to facilitate analysis (Bobko, Roth & Buster, 2007; McGahan et al., 1986). Each construct for which composite scores were calculated was considered a reflective construct, lending support to the method of composite score calculation.

Study 1 Results

Convergent and Discriminant Validity Evidence

Table 2 and S3 present the average and overall convergent and discriminant relations based on current and ideal occupations. In terms of convergent relations for knowledge, participants' ratings of occupational knowledge were positively related to the corresponding knowledge area of their current and ideal occupation (average convergence index = 0.26, ranging from 0.12 to 0.47 for the current occupation; average convergence index = 0.23, ranging from 0.06 to 0.37 for the ideal occupation, respectively). Similarly, participants' ratings of occupational skills were positively related to the corresponding area of their current and ideal occupation (average convergence index = 0.20, ranging from 0.06 to 0.38 for the current occupation; average convergence index = 0.18, ranging from 0.08 to 0.33 for the ideal occupation, respectively). These correlations indicate that participants' knowledge ratings substantially converge with current and ideal occupations more than occupational skills. Nonetheless, participant ratings of both knowledge and skills showed expected convergent relations with the corresponding knowledge and skills reflected in their current and ideal occupations, supporting the convergent validity of the measure.

In terms of discriminant relations for knowledge, correlations with corresponding knowledge areas were substantially higher than the average correlation with non-corresponding knowledge areas (average discrimination index = 0.22, ranging from .09 to .42 for the current occupation; average discrimination index = .20, ranging from .05 to .35 for the ideal occupation, respectively). Similarly, correlations with corresponding skills were substantially higher than the average correlation with non-corresponding skills (average discrimination index = .16, ranging from .01 to .36 for the current occupation; average discrimination index = .16, ranging from .07 to .32 for the ideal occupation, respectively). These findings indicate that the OSKI showed the expected pattern of discriminant relations with non-corresponding occupational variables based on current and ideal occupations, which further provided construct validity evidence.

Criterion-Related Validity Evidence for Predicting Subjective Career Outcomes

Next, we investigated the OSKI's criterion-related validity by examining the relations between participants' person-occupation knowledge and skills fit with their subjective career outcomes. Here, we operationalized person-occupation fit via profile correlations between participants' knowledge and skills scores and their current occupations. This method, which is based on profile correlations, has been used by other popular inventories measuring individual differences, such as the O*NET Interest Profiler (Rounds et al., 2021). Also, this approach has been shown to produce stronger predictive power on career outcomes vs. other techniques (Xu & Li, 2020). Table 3 presents the results for person-occupation fit based on knowledge and skills in predicting subjective career outcomes. As shown, for both knowledge and skills, the fit between individuals and their current occupation was positively related to career choice satisfaction and fit perceptions. Knowledge fit reported the strongest correlation with demands-abilities fit (r = .21) and the weakest correlation with person-organization fit (r = .09). Additionally, moderate correlations were found for knowledge fit with needs-supplies fit (r = .16) and career choice satisfaction (r = .20). For correlations between skills fit with subjective career outcomes, the highest correlation was found with demands-abilities fit (r = .14) and the lowest correlation with person-organization fit (r =.02). More modest effects were found for career choice satisfaction (r = .11) and needs-supplies fit (r = .08). These trends in the results align closely with the central propositions of demands-abilities fit theory which stresses on the congruence between job requirements and skills (Edwards, 1991). Thus, we expected that individuals with better knowledge and skills fit with their current occupation would have shown positive subjective career outcomes, especially with specific outcomes like demand-abilities fit. Overall, congruence in terms of occupational knowledge reported the highest concurrent validity with subjective career outcomes compared to occupational skills. We expected these results as, for some careers, specific knowledge competencies are required, whereas some skills can be transferrable across various occupations.

As an additional test, we calculated fit using all items of the occupational knowledge and skill scale and compared its predictive validity separately for knowledge and skills items. This method was included in order to include the approach used by the *Skills Matcher* to compare results and determine whether combining domains vs. using individual domain profile correlations yields stronger predictive relations. The results obtained for these combined analyses indicated that skills and knowledge fit had the strongest profile correlation with demands-abilities fit (r = .22) and the weakest profile correlation with person-organization fit (r =.07). More positive modest results were found for fit with career choice satisfaction (r = .19) and Needs-supplies fit (r = .15). These results indicated that looking at each domain independently is the more appropriate approach. In general, the positive profile correlations support past research findings. In particular, past research has shown that individual perceptions of perceived fit with occupation are tied closely to career outcomes such as career choice satisfaction and needs-supplies fit (Lauver & Kristof-Brown, 2001). Furthermore, these results further solidified the core ideas purported by theories of person-environment fit and their role in determining career outcomes (Resick et al., 2007).

Exploratory Factor Analysis for Knowledge & Skills

Tables 4 and 5 report the results of the exploratory factor analysis, showing the eigenvalues and the pattern matrix for the initial skills and knowledge items used in Study 1. A parallel analysis was run before each EFA for skills and knowledge using sample 1 – Prolific). This type of analysis was chosen for supplementary data analysis to obtain supporting information regarding the structure of the items. However, these results did not affect the measure development process because we adapted single-item scales. Based on the results of the parallel analysis conducted for the 19 skills items, it was suggested that four factors should be retained. Furthermore, all four factors have eigenvalues more significant than one which adheres to Kaiser's criterion (Kaiser, 1960). After conducting an EFA with four factors, these 4 factors together accounted for 50% of the variance. The first skill factor consisted of 8 items that primarily measured interpersonal skills, with social perceptiveness and social coordination having the highest loadings. The second skills factor consisted of 5 items that primarily measured technical skills, with technology design and programming reporting the highest loadings. The third skills factor consisted of 3 items that measured physical skills, with body coordination and finger dexterity having the highest loadings. Lastly, the final skills factor also consisted of 3 items that measured creativity skills, with creative thinking and complex problem solving showing the highest loadings.

For the parallel analysis conducted on the 27 knowledge items – the parallel analysis suggested that the number of factors to be retained is 6. The EFA results for these six factors together explain 52% of the variance. The first knowledge factor consisted of 6 items that measured realistic knowledge, with construction and transportation showing the highest loadings. The second knowledge factor consisted of seven items that measured people operations with customer service and managing others, showing the highest loadings. The third knowledge factor contained four items that looked at physical sciences; biology and chemistry reported the highest loadings among these. The fourth knowledge factor measured artistic knowledge and consisted of two items – design and fine arts that both had high loadings. The fifth knowledge factor measured math-intensive knowledge from a total of 4 items; engineering and technology, as well as mathematics, had the highest loadings. Lastly, the final knowledge factor measured social sciences and contained four items, with psychology, sociology, and anthropology showing extremely high loadings. Altogether, these results show that the skills and knowledge items included in our measure are a part of factors that could be used to develop scales with multiple items. However, as noted, our primary focus was to assess person-occupation fit using single items that directly map into corresponding O*NET variables, similar to how the Career One Stop *Skills Matcher* works in practice.

Study 1 Summary and Discussion

In Study 1, we adapted and validated the Occupational Skills and Knowledge Inventory, which was explicitly used for item-level matching similar to previous measure validation studies (Maples-Keller et al., 2019), and we retained a total of 46 items (knowledge and skills). One of the major findings is that the fit measure, including all knowledge and skills, did not have a substantial predictive advantage over the individual occupational knowledge or skills item scales for profile correlations. These findings suggest that calculating person-occupation fit based on knowledge and skills separately is more effective in predicting career outcomes than combining the two domains into a single profile, which is the approach taken by the *Skills Matcher*. Thus, in Study 1, the results indicated strong preliminary concurrent validity for the OSKI. In Studies 2 and 3, we replicate and extend the validity and reliability analyses conducted in Study 1 using our 46-item OSKI. We incorporated additional analyses such as predictive validity (longitudinal) and retest reliability across two unique samples - common users of career exploration tools (i.e., recent university and community college graduates entering the workforce) with follow-ups during six and eight months, respectively.

Studies 2 and 3

Participants and Procedures

Sample 2

Sample 2 was drawn from recent bachelor's degree graduates from three U.S. universities who were emailed about the study. At Time 1, 919 participants responded to the survey. After removing cases where participants failed quality control questions, the final sample contained 816 participants. Of these, there were 73.0% female and 24.9% male. The average age was 22.6 *(SD=2.6)*. After six months, participants in the first wave were contacted again to respond to a follow-up survey. At Time 2, 397 participants provided sufficient responses (response rate: 48.7%). Tables S4 & S5 report key demographic information and characteristics of sample 2 and sample 3 participants, respectively.

Sample 3

Sample 3 contained 584 participants drawn from a unique population of community college graduates and contacted via email at Time 1. After conducting quality checks, the final sample consisted of 560 participants. Among them, 79.1 % were female and 16.2 % were male. The average age was 24.7 *(SD=7.6)*. Respondents from Time 1 were followed longitudinally 8 months later to participate in a follow-up survey after the first wave of data collection as done in prior research (Donnellan et al., 2006). Of these participants, 277 provided adequate responses at Time 2.

In Samples 2 and 3, participants were compensated with a $10 Amazon gift card for completing each wave. Tables S4 and S5 in the Supplemental material provide demographic information on Samples 2 and 3.

The procedure consisted of the collection of validity evidence with regards to convergent validity and fit as conducted in Study 1. Additionally, longitudinal data was collected by assessing test-retest *reliability* by looking at profile reliability and rank-order stability based on participant self-reports.

Measures and Analytic Strategy

The same measures from Study 1 were used in Studies 2 and 3 - the 46-item OSKI, the Academic Major Satisfaction Scale by Nauta (2007), and the nine fit items from Cable and DeRue (2002). To provide clarity for our survey participants, we adjusted the question wording for the ideal occupation from the initial survey to "What job would you most like to have after graduating?" Additionally, students who reported having a job at the follow-up waves were asked to input information regarding their current job titles. The occupational coding for Studies 2 and 3 was coded by undergraduate research assistants who used Study 1's occupational coding as a guide in order to input data for current and ideal occupations. Once initial coding was completed, two graduate students reviewed the occupational coding results and reported 96% agreement. Then, using the established coding guide from the initial survey, the same graduate students mapped participant responses from the follow-up survey into O*NET occupations. Next, we discuss the results of Studies 2 and 3 collectively.

Studies 2 and 3 Results and Discussion

Convergent and Discriminant Evidence with Current and Ideal Occupations

Table 2 displays average convergent and discriminant indexes for Study 2 and Study 3 participants for the OSKI scale. Tables S6 and S7 in the supplemental materials contain more detailed individual convergent and discriminant evidence for each item in both studies. We first examined convergent relations for knowledge and found that these relations were positively correlated with corresponding knowledge areas for current occupation. For current occupation with the knowledge dimensions, there was an average convergence index of .24 (*SD* = .10) with ranges of .07 to .57 in sample 2 and in sample 3, an average of .14 (*SD* =.11) with ranges of -.03 to .52. Based on the results, convergence between corresponding knowledge areas and current occupations were higher for Study 2 vs. Study 3 – this is evident in the averages as well as the maximum range value for Study 2. There was a higher average convergence index for ideal occupations and knowledge in Study 2 vs. current occupations. The average convergent indices for Studies 2 and 3 were .33 (*SD* = .16) with ranges of .09 to .67 in sample 2 and .05 (*SD* =.10) with ranges of -.18 to .25 in sample 3. With respect to the current occupation and skills, results showed that the average convergence indexes of .15 (*SD* =.07) with ranges of .07 to .30 in sample 2 and .07 (*SD* = .06) with ranges of -.04 to .18 in sample 3.

For the ideal occupation and skills, the average convergence indices were .19 (*SD* = .12) with ranges of (.01 to.52) in sample 2 and .00 (*SD* =.09(-.11 to .18) in sample 3, respectively. Based on the results for the corresponding skills categories, it is consistent with the trends shown in knowledge results, which showed a higher average for ideal occupation than current occupation but also higher averages for Study 2 vs. Study 3. These findings replicate the pattern of results generated in Study 1, which indicates that based on Studies 2 and 3's findings, the OSKI also shows validity evidence.

Discriminant relations of participants for Studies 2 and 3 can be found in Table 2 (with complete results presented in the Supplementary materials), Tables S6-S7. In general, results revealed higher correlations between corresponding occupational knowledge and skills categories (convergent validity) and lower, in some cases, negative correlations with non-corresponding knowledge and skills categories (discriminant validity) across current and ideal occupations. For current occupation and knowledge, the average discriminant index was .16 (*SD* = .09) in Study 2 and in Study 3, an average discriminant index of .06 (*SD* = .11). Among ideal knowledge, the average discriminant indices were 0.22 (*SD* = .15) and -.04 (*SD* =.11) in Studies 2 and 3 respectively. Based on the results for skills, correlations with corresponding skills were substantially higher than the average correlation with non-corresponding skills. In Study 2, the average discrimination index = .08 (*SD* = .08), and in Study 3 it was .00 (*SD* = .06) for the current occupation. For ideal occupation, we obtained larger but weak average discriminant indices of .11 (SD =.14) for sample 2 and -.08 (*SD* = .09) for sample 3. Based on these findings, we can deduce the OSKI shows discriminant validity.

Profile Reliability and Test-Retest Reliability Evidence

Reliability results for Studies 2 and 3 can be found in Table 4. For all 46 (19) skills and (27) knowledge items in the OSKI, we calculated test-retest reliability scores and profile reliabilities. These scores were computed using subsets of participants who provided valid responses at T1 and T2 (Study 2 – six months later and Study 3 – eight months later). These profile reliabilities generally reflected the average correlation among each participant's knowledge or skills profile with their knowledge or skill profile measured at a future time. For

Sample 2, the knowledge profile reliability was .70, and for Sample 3, it was .67. The skills profile scores in Sample 2 were .69 and .68 for Sample 3. These profile reliability scores indicated consistency in participants' profiles over time. Additionally, the retest reliabilities reflected the rank-order stability of each knowledge or skill item, measuring whether participants who score higher on a particular knowledge/skill item at a one-time point also score higher at a future time point. For Sample 2, the test-retest reliabilities ranged from .41 (Transportation) to .80 (Biology) for knowledge items. For skills items, test-retest reliabilities in Sample 2 ranged from .41 (Social Coordination) to .74 (Programming). In Sample 3, test-retest reliabilities ranged from .41 (Production and Processing) to .79 (Medicine and Dentistry) for knowledge items. The range of test-retest reliabilities for skills items was .40 (Social Perceptiveness) to .67 (Physical Strength, Science). Overall, these results highlight that the OSKI is a reliable assessment of knowledge and skills profiles and items over time.

Criterion-Related Validity Evidence for Predicting Subjective Career Outcomes

Lastly, we investigated the OSKI's predicative criterion-related validity by examining the relationship between participants' person-occupation knowledge and skills fit with their subjective career outcomes measured at follow-up waves, as shown in Tables 2 and 3. Here, we operationalized person-occupation fit via profile correlations between participants' knowledge and skills scores and their current occupations at Time 1 (T1) and Time 2 (T2). This method, which is based on profile correlations (Table 2), has been used by other popular inventories measuring individual differences, such as the O*NET Interest Profiler (Rounds et al., 2021). Also, as mentioned before, this approach is superior to others due to its propensity to produce stronger predictive power on career outcomes (Xu & Li, 2020). In order to ensure clarity, Study 2 results will be reported before the slash, and Study 3's results will be reported after the slash.

Table 3 presents the results for person-occupation fit based on knowledge and skills in predicting subjective career outcomes. Like Study 1's results, the average profile correlations between current occupations and participants' knowledge and skills were positive. Knowledge profile correlations for current occupation were *r* = .27/17 with SD = .34/.31. Additionally, the results were similar for ideal occupation and knowledge with profile correlations scores of r= .37/.20 and SD=.37/.32. This pattern was also apparent for profile correlations between skills and current as well as ideal occupation. For current occupations– the following values were found *r* = .15/.07 with SD = .34/.32, and for ideal occupation – *r* = .22/.10 and SD =.22/.32.

Furthermore, predictive validity evidence is displayed in Table 3 for both knowledge and skills fit. In Study 2, knowledge fit reported the strongest correlation with demands-abilities fit (*r* = .20) and the weakest correlation with person-organization fit (*r* = .04), similar to the results obtained in Study 1. More modest correlations were found for knowledge fit with career choice satisfaction (*r = .11)* and needs-supplies fit (*r* =.09). However, in Study 3, knowledge fit also reported the strongest correlation with demands-abilities fit (*r* = .18). Knowledge fit still showed the weakest correlation with needs-supplies fit (*r* = .16). Additionally, moderate correlations were found for knowledge fit with person-organization (*r* = .17) and career choice satisfaction (*r* = .17). For correlations between skills fit with subjective career outcomes, the highest correlation was found with career choice satisfaction (*r* = .12) and the lowest correlation with Person-organization fit and demands-abilities fit (*r* =.05) in Study 2. More modest effects were found in needs-supplies fit (*r* = .08). In Study 3, the highest correlation was found between skills fit and demands-abilities fit (*r* =.29*)* and the lowest with person-organization fit (*r*=.09). More moderate correlations were found with career choice satisfaction (*r* =.13) and with needs-supplies fit (*r* = .20). Similar to Study 1, the strong correlations with demands-abilities fit support the central components of demands-abilities fit theory which stresses on the congruence between job requirements and skills (Edwards, 1991). Thus, we expected that individuals with better knowledge and skills fit with their current occupation would have shown positive subjective career outcomes, especially with specific outcomes like demand-abilities fit. Overall, congruence in terms of occupational knowledge reported the highest concurrent validity with subjective career outcomes compared to occupational skills. We expected these results as, for some careers, specific knowledge competencies are required, whereas some skills can be transferrable across various occupations. Nevertheless, based on these findings, we find support that the OSKI shows predictive validity.

Similar to Study 1, we calculated fit using all items of the occupational knowledge and skill scale collectively with the previously discussed subjective career outcomes. This method assessed further and provided evidence for using a combination of domains (as used by the *Skills Matcher*) vs. using individual domain profile correlations to obtain predictive relations. The results obtained for these combined analyses indicated that skills and knowledge fit had the strongest profile correlations with demands-abilities fit (r = .15) / (r = .25) across both studies 2 and 3 respectively and the weakest profile correlations with person-organization fit (r =.04)/ (r =.14). More positive modest results were found for fit with career choice satisfaction (r = .13)/ (r =.17) and needs-supplies fit (r = .11)/ (r =.18). Thus, these results provide additional support for the using the approach of looking at each domain independently. Moreover, the positive profile correlations support past research findings. The findings show evidence of relations between perceived fit and subjective career outcomes while aligning with the core ideas of relevant fit theories (Lauver & Kristof-Brown, 2001; Resick et al., 2007).

Studies 2 and 3 Summary

Studies 2 and 3 extended and enhanced the results of Study 1 through the use of longitudinal samples – graduates from both 4-year universities (Study 2) and community colleges (Study 3). Thus, this methodological decision supported the OSKI's reliability and validity. The measure showed a reliable internal structure through strong profile reliability found at 6 months (Study 2) and 8 months (Study 3) and rank-order stability across samples and time. Additionally, the OSKI displayed convergent and discriminant validity similar to Study 1, as participants' skills and knowledge were positively correlated with their corresponding occupational ratings for their current and ideal careers. Finally, participants' skills and knowledge fit results indicated stronger predictive power with subjective career outcomes, which provides support for the use of a measure like the OSKI, which maps directly onto O*NET occupational data that treats knowledge and skills as two separate domains, unlike its predecessor the Career One Stop *Skills Matcher*.

General Discussion

The current research adapted the Occupational Skills and Knowledge Inventory (OSKI, a 46 single item-scales based on Career One Stop's Skills Matcher, which directly maps into the Occupational Information Network's occupational knowledge, skills, and abilities (O*NET). Drawing data from three samples, we first adapted and refined knowledge, skills, and abilities items (KSA), identifying and including 13 new items, after conducting psychometric analyses and content considerations. Then, we conducted a series of assessments in order to investigate the reliability and validity of the OSKI to determine its overall utility in both research and applied contexts. Based on this study's findings, the OSKI is an integrative, reliable, and valid KSA measure. By providing detailed information about the measure development and validation process, our results addressed a major shortcoming which may have posed a research gap for researchers seeking to replicate pre-existing knowledge and skills scales in the past.

Overall, our measure and findings can serve several purposes. First, the measure can be adapted for public domain websites to help people explore careers based on their knowledge and skills. The ultimate benefit of the OSKI lies in its output data as participants are provided with a list of prospective careers relevant to their level of KSA reported on the measure, which will also be linked to O*NET occupational data in order to highlight those with bright outlooks etc. (U.S. Department of Labor Employment and Training Administration, 2023). As the study's results suggested, skills and knowledge fit should be evaluated separately due to the lack of substantial advantage presented by collectively looking at these fit measures. Such a technique permits the generation of a separate list for each domain, which can further assist with career exploration. The logic is that these lists can give individuals a better idea of how their knowledge and skills fit are independently connected to their career outcomes such as person-organization fit, needs-supplies fit, and demands-abilities fit. Such information is crucial to career explorations as it presents an opportunity to look at relevant knowledge, skills, and abilities critical for fit or misfit with based on career outcomes (Bretz, 1984; Carless, 2005; Kristof-Brown et al., 2013).

Second, our results can inform and tailor educational and workplace interventions that aim to match people to skill and knowledge demands in the current and future labor market. Such matching is crucial for those contemplating career changes and those exploring competencies essential to promote upskilling and reskilling successfully. The idea is that individuals, in most circumstances, self-select into occupations that match their current skills and knowledge (Kristof-Brown et al., 2013). Thus, convergent and discriminant relations provide insight into how skills and knowledge converge with corresponding O*NET skills and knowledge occupational variables as a result of their person-level self-reports collected. For example, an individual with current knowledge in medicine may gravitate to a field where this knowledge is required. However, their level of knowledge in the area and other factors, such as job requirements, may determine their specific profession in the field. More importantly, looking at such relations can also serve as a guide for individuals regarding their compatibility and areas in which they may need to expand their expertise to be qualified for specific roles. This aspect of addressing the gaps in expertise and the OSKI directly highlighting the required levels of competencies for the particular position serves as a direct reference of comparison, which can guide upskilling and reskilling endeavors within broad occupational groups. Furthermore, these applications may benefit community college students (Study 3) who showed a lower fit with their occupations than the other samples. However, variations in fit also provided implications for specific differences found in career outcomes, as discussed in the previous paragraph.

Finally, our findings inform theories of person-environment fit by comparing the differing roles of skills and knowledge fit in shaping and improving career outcomes (Bretz, 1984; Carless, 2005; Kristof-Brown et al., 2013). For example, our initial results suggested that the fit between employees and their occupation in terms of knowledge is a stronger predictor of subjective career outcomes than fit between employees' skills and occupational demands. Such results can be applicable in decision-making processes that require consideration of individual differences in levels of skills and knowledge in relation to career choices and academic endeavors. To a smaller extent, this study's research provides additional support for the propositions proposed by person-environment fit theories because, though it was not a primary goal, this component of fit is assessed among the three datasets. Thus, it adds to the academic discussion that fit varies but, in this case, specifically the relationship between fit with knowledge, skills, and abilities. Ultimately, these conclusions are drawn as due to our use of a multi-study method with various samples which directly reduces issues related to range restriction and finding support for prepositions of fit with other constructs.

Strengths, Limitations, and Future Directions

The Occupational Skills and Knowledge (OSKI) is the 46-item measure with single-item scales adapted based on Career One Stop's *Skills Matcher*, which provides publicly available documentation on the development process and its adherence to psychometric properties, unlike its predecessor that connects directly to the O*NET occupation database. Additionally, one of the measure's main strengths lie in its use of extensive data from three distinct samples (one representative of the U.S population), two of which are samples of recent graduates obtained from U.S universities and community colleges as they transition from school to the workplace. These sample participants are highly diverse regarding demographic factors such as age, race/ethnicity, and gender. Moreover, the inclusion of longitudinal data in Studies 2 and 3 supplements the data on concurrent validity and highlights the OSKI's predictive validity. Beyond its validity, the OSKI displayed strong reliability evidence (profile reliability and rank-order stability), which is essential in the discussion of psychometric properties as it has been shown to give relatively consistent results across time and samples. Lastly, the data collected from community college graduates provided more extensive insights due to difference in educational experiences vs. other samples which indicates that our measure can be used and relevant across various post-secondary participants.

Nevertheless, though the measure has several strengths, discussing several limitations and future directions the research proposes is crucial. First, the study used self-reports across all three samples, which may raise concerns due to its propensity for social desirability in responding to assessments (Holtgraves, 2004; Podsakoff et al., 2003). However, despite these concerns – studies have shown that individuals generally have accurate views of their knowledge, skills, and abilities. As such, there has been evidence that self-ratings like objective-score pairings consist of substantial convergent and discriminant validity (Ackerman et al., 2002; Sitzmann et al., 2010). Moreover, using self-reported knowledge and skills allows for more variables to be captured at a faster rate, which is useful for researchers who are faced with time and economic constraints but still seek to collect quality data. Nevertheless, future research can build on the current research, looking at comparisons in convergent and discriminant validity of self-reports of skills and knowledge vs. test-based skills and knowledge in order to provide further evidence on the integrity of using self-reports in research.

Second, due to our inclusion of single-item scales that map into the O*NET, questions may arise regarding the quality of the O*NET occupational data. The O*NET's occupational data is a compilation of data collected from job incumbents, occupational analysts, and other subject matter experts, which may not be perfect depictions of all jobs within industries and occupations (Peterson et al., 2001). Regardless, the additional occupational coding step incorporated in our study using trained coders was needed to place job titles reported into broader O*NET occupations for analyses to be conducted effectively. Despite this limitation, the O*NET continues to be deemed a comprehensive, standardized source of updated occupational information in the United States (National Research Council, 2010; Peterson et al., 2001). Thus, future research can build on our study not only via replication, as there is now access to a valid, reliable item pool from which small or larger scales can be derived, as done in prior research (Maples-Keller et al., 2019). Moreover, in prospective research, international occupational databases can be adapted to address the shortcomings of the O*NET or O*NET ratings for more specific job or organization contexts can be included.

Lastly, our study contains longitudinal data in Studies 2 and 3 from recent university and community college graduates, where outcome data was collected relatively soon after job commencement. Two concerns may arise – the first is that the outcome data collected solely reflects views of those in their early career development phase, which are subjected to change as time and experience within the workforce increase (Hollywood et al., 2020). Similarly, the argument may extent further to argue that outcome data account mainly for the “honeymoon phase” (Smith et al., 2017) among new graduates, especially those with great experiences or are eager to begin their new life journey. This period is said to last 6 months, and we followed our Sample 3 for more than six months and this can be an additional concern which is related to the first one highlighted above. Nevertheless, the data from this study can be expanded and used in longitudinal studies that follow its participants for longer periods to obtain more in-depth information, as data from every stage of career development can assist organizations and institutions as they hire and matriculate newcomers into their organizational climate and culture.

Conclusion

This study developed and adapted the Occupational Skills and Knowledge Inventory (OSKI), a 46-item measure with single-item scales that connect directly to O*NET’s occupational data for skills, knowledge, and abilities. Though adapted from the Career One Stop *Skills Matcher*, the OSKI retained and included 13 new items that evaluated skills, knowledge, and abilities. Unlike its predecessor, the OSKI provides evidence of its strong validity and reliability as a measure. Ultimately, the OSKI is an adequate and necessary career exploration measure that has the potential to address the needs of the current and future labor market as a guide in educational and organizational settings to assist in college major exploration, upskilling, and reskilling efforts as well as several other research and applied context.

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TABLES

Table 1.

The OSKI (Occupational Skills and Knowledge Inventory) Questionnaire and scoring information (adapted from CareerOne Stop Skills Matcher)

Beginner	Basic	Skilled	Advanced	Expert
1	2	3	4	5

Knowledge areas

The next set of questions asked about your knowledge in various subjects. Think and respond honestly about your knowledge relative to other people.

How much do you **know** about:

Biology: plant, animal, and cell functions
Chemistry: chemical processes and their applications
Communications and Media: conveying information using written, oral, and visual media
Computers and Electronics: computer hardware and software, including applications and programming
Construction: building materials, methods, and tools
Customer Service: handling customer needs and resolving service problems
Design: designing techniques, tools, and principles
Economics and Accounting: principles and practices of accounting, economics, and financial markets
Engineering & Technology: practical applications of engineering science and technology
Fine Arts: developing art forms, such as music, painting, or drama
Food Production: planting, growing, and harvesting food products
Law & Government: legal codes, court procedures, government regulations, and political processes
Managing others: leading other people and business planning
Mathematics: using arithmetic, algebra, geometry, calculus, and statistics
Mechanics: designing, using, repairing, and maintaining machines
Medicine and Dentistry: providing health care
Office Work: completing administrative and clerical work, such as word processing and managing records
Personnel and Human Resources: principles and procedures for recruiting, hiring, and training employees
Physics: physical principles, laws, and their applications
Production and Processing: overseeing manufacturing and distribution processes
Psychology: methods of research, assessment, and treatment of human behavior
Public Safety and Security: equipment, procedures, and strategies to promote security operations
Sales and Marketing: promoting and selling products or services
Sociology and Anthropology: theories of group behavior, societal trends, and human culture
Teaching and Course Design: applying methods and principles of instruction
Therapy and Counseling: applying principles and methods used in counseling

Transportation: principles and methods for moving people or goods by air, rail, sea, or road

Table 1 Continued

Skills:

The next set of questions asked about your workplace skills. Think and respond honestly about your skills relative to other people.

How **skilled** are you at:

Body Coordination: moving your arms, legs, and body together
Complex Problem Solving: figuring out the best way to solve a difficult problem
Creative Thinking: developing original ways to solve a problem
Financial Management: determining how money be spent to get work done
Finger Dexterity: controlling your fingers to precisely to manipulate small objects
Helping People: understanding how to help others in need
Instructing: teaching people how to do something
Persuasion: convincing others to change their minds or behavior
Physical Strength: using muscle force to lift, push, pull, or carry objects
Programming: writing computer programs for various purposes
Repairing: fixing machines using tools
Science: using scientific rules and methods to solve problems
Social Coordination: Adjusting actions in relation to others' actions
Social Perceptiveness: understanding others' reactions and behaviors
Speaking: talking to others to convey information effectively
Technology Design: building and adapting new technology
Time Management: managing your own time and the time of others
Troubleshooting: identifying and fixing problems in machines or technology
Writing: communicating effectively in writing

Note. Corresponding O*NET variables for knowledge measures are from the knowledge domain. Corresponding O*NET variables for skill measures are from the abilities and skills domain.

Items 1, 5-6, 10, 13, 15-18, 20-22, 24-26, 28-29, 33-34, 37-39, 42, 44-46 were adapted from: U.S. Department of Labor Employment and Training Administration. CareerOneStop, Retrieved July 29, 2022, from https://www.careeronestop.org/.

Scoring Instructions

Items 1-27 are knowledge items, and items 28-46 are skills items.

Table 2.

Convergent and Discriminant Correlations with Current and Ideal Occupations

	Study 1 Adults (n = 768)		Study 2 University Graduates (n = 816)		Study 3 Community College Graduates (n = 590)	
	M (r)	*SD*	*M (r)*	*SD*	*M (r)*	*SD*
Occupational Knowledge						
Current Occupations						
Convergent Correlation	.26	.08	.24	.10	.14	.11
Discriminant Correlation	.22	.08	.16	.09	.06	.11
Profile Correlation	.31	.33	.27	.34	.17	.31
Ideal Occupations						
Convergent Correlation	.23	.09	.33	.16	.05	.10
Discriminant Correlation	.20	.09	.22	.15	-.04	.11
Profile Correlation	.27	.32	.37	.37	.20	.32
Occupational Skills						
Current Occupations						
Convergent Correlation	.20	.09	.15	.07	.07	.06
Discriminant Correlation	.16	.08	.08	.08	.00	.06
Profile Correlation	.21	.35	.15	.34	.07	.32
Ideal Occupations						
Convergent Correlation	.18	.08	.19	.12	.00	.09
Discriminant Correlation	.16	.08	.11	.14	-.08	.09
Profile Correlation	.21	.35	.22	.22	.10	.32

Note. For occupational knowledge and skills, convergent correlations were calculated between pairs of participants' knowledge/skills (e.g., Biology) and corresponding knowledge/skill dimensions from O*NET (e.g., Occupational Biology scores) of their current or ideal occupations. Discriminant Indices were calculated by subtracting the average of all non-corresponding knowledge/skill correlations (e.g., Biology with Fine Arts) from the convergent correlations of their current or ideal occupations.

Table 3.

Criterion-Related Validity Evidence for the OSKI

	Career Choice	P-O Fit	N-S Fit	D-A Fit
Study 1- Adult Sample (Concurrent Validity, n=768)				
Knowledge Fit	.20	.09	.16	.21
Skills Fit	.11	.02	.08	.14
Knowledge and Skills Fit	.19	.07	.15	.22
Study 2 – University Graduates (HOPS) (Predictive Validity, *n=416*)				
Knowledge Fit	.11	.04	.09	.20
Skills Fit	.12	.05	.08	.05
Knowledge and Skills Fit	.13	.04	.11	.15
Study 3- Community College Graduates (CCSS) (Predictive Validity, *n*= 277)				
Knowledge Fit	.17	.17	.16	.18
Skills Fit	.13	.09	.20	.29
Knowledge and Skills Fit	.17	.14	.18	.25

Note. Career Choice = Career Choice Satisfaction; P-O Fit = Person-Organization Fit; N-S Fit = Need-Supply Fit; D-A Fit = Demands-Abilities Fit. Both occupational skills and knowledge are represented by profile correlations between participants' knowledge and skills profiles and those of their current occupations. Occupational information in Study 2 and Study 3 are collected in follow-up surveys at six and eight months.

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Table 4.

Occupational Knowledge EFA Model Fit in Study 1.

	Item	Realistic	People Operations	Physical Sciences	Artistic Knowledge	Math-Intensive	Social Sciences
K5	Construction	**0.67**	-0.01	0.12	0.20	0.29	-0.01
K27	Transportation	**0.61**	0.20	0.11	0.03	0.24	0.14
K22	Public Safety and Security	**0.59**	0.19	0.11	0.05	0.19	0.33
K20	Production and Processing	**0.58**	0.28	0.09	0.05	0.25	0.15
K15	Mechanics	**0.51**	0.06	0.16	0.32	0.44	-0.04
K11	Food Production	**0.50**	0.15	0.21	0.00	-0.01	0.19
K6	Customer Service	0.13	**0.63**	0.07	0.07	-0.13	-0.03
K13	Managing Others	0.25	**0.63**	0.06	0.15	0.19	0.16
K18	Personnel and Human Resources	0.27	**0.58**	0.03	-0.03	0.08	0.37
K23	Sales and Marketing	0.28	**0.54**	0.05	0.02	0.08	0.15
K3	Communications and Media	0.02	**0.54**	0.00	0.28	0.12	0.19
K17	Office Work	-0.07	**0.50**	-0.05	-0.02	0.15	0.05
K25	Teaching and Course Design	0.13	**0.41**	0.07	0.33	0.18	0.35
K1	Biology	0.13	0.04	**0.78**	-0.01	0.11	0.26
K2	Chemistry	0.20	0.01	**0.76**	0.02	0.37	0.17
K19	Physics	0.31	0.00	**0.51**	0.15	0.50	0.14
K16	Medicine and Dentistry	0.20	0.03	**0.43**	-0.01	-0.01	0.42
K7	Design	0.22	0.32	0.04	**0.50**	0.36	0.05
K10	Fine Arts	0.11	0.10	-0.01	**0.43**	0.10	0.24
K9	Engineering and Technology	0.35	0.01	0.20	0.21	**0.69**	0.05
K14	Mathematics	0.10	0.20	0.32	0.03	**0.61**	-0.01
K4	Computer and Electronics	0.17	0.10	0.02	0.11	**0.56**	0.02
K8	Economics and Accounting	0.25	0.42	0.01	-0.33	**0.51**	0.16
K21	Psychology	0.09	0.08	0.21	0.13	0.00	**0.81**
K24	Sociology and Anthropology	0.11	0.16	0.17	0.06	0.05	**0.72**
K26	Therapy and Counseling	0.12	0.26	0.11	0.27	-0.03	**0.64**
K12	Law and Government	0.27	0.24	0.06	-0.21	0.27	**0.45**

Note. The knowledge EFA model contains 27 basic occupational knowledge items from the OSKI, which load onto six factors based on the parallel analysis results. **Bolded values** indicate statistically significant correlations for each factor loading.

Table 5.

Occupational Skills *EFA Model Fit in Study 1.*

	Item	Interpersonal Skills	Technical Skills	Physical Skills	Creativity Skills
S33	Social Perceptiveness	**0.82**	0.00	0.10	0.09
S32	Social Coordination	**0.80**	0.03	0.15	0.11
S15	Helping People	**0.68**	-0.02	0.16	0.13
S35	Speaking	**0.58**	0.02	0.22	0.37
S17	Instructing	**0.56**	0.13	0.16	0.41
S25	Persuasion	**0.52**	0.21	0.14	0.35
S40	Time Management	**0.48**	0.16	0.13	0.28
S11	Financial Management	**0.36**	0.27	0.10	0.18
S38	Technology Design	0.08	**0.75**	0.07	0.12
S27	Programming	-0.04	**0.70**	0.01	0.04
S41	Troubleshooting	0.09	**0.68**	0.17	0.16
S28	Repairing	-0.01	**0.65**	0.32	0.08
S30	Science	0.14	**0.53**	0.03	0.22
S3	Body Coordination	0.19	0.05	**0.82**	0.06
S13	Finger Dexterity	0.18	0.15	**0.57**	0.13
S26	Physical Strength	0.21	0.31	**0.50**	0.07
S6	Creative Thinking	0.23	0.27	0.12	**0.67**
S5	Complex Problem Solving	0.26	0.35	0.08	**0.63**
S42	Writing	0.37	0.04	0.06	**0.50**

Note. Skills EFA models contain 19 basic occupational skills items from the OSKI, which load onto four latent factors based on the parallel analysis results. **Bolded values** indicate statistically significant correlations for each factor loading.

Table 6.

Rank-order Stability (Test Retest) Evidence for Study 2 and Study 3.

	Study 2 (*r*)	**Study 3 (*r*)**		**Study 2 (*r*)**	**Study 3 (*r*)**
Knowledge profile	**0.70**	**0.67**	**Skills profile**	**0.69**	**0.68**
Biology	0.80	0.69	Body Coordination	0.67	0.65
Chemistry	0.79	0.68	Complex Problem Solving	0.45	0.56
Communications and Media	0.52	0.50	Creative Thinking	0.61	0.61
Computers and Electronics	0.72	0.61	Financial Management	0.67	0.55
Construction	0.63	0.64	Finger Dexterity	0.57	0.55
Customer Service	0.64	0.66	Helping People	0.59	0.59
Design	0.54	0.45	Instructing	0.55	0.55
Economics and Accounting	0.73	0.66	Persuasion	0.51	0.52
Engineering & Technology	0.74	0.66	Physical Strength	0.66	0.67
Fine Arts	0.68	0.68	Programming	0.74	0.44
Food Production	0.56	0.60	Repairing	0.61	0.62
Law & Government	0.63	0.59	Science	0.73	0.67
Managing others	0.56	0.67	Social Coordination	0.41	0.46
Mathematics	0.73	0.73	Social Perceptiveness	0.51	0.40
Mechanics	0.71	0.65	Speaking	0.56	0.53
Medicine and Dentistry	0.75	0.79	Technology Design	0.62	0.53
Office Work	0.61	0.65	Time Management	0.51	0.53
Personnel and Human Resources	0.45	0.57	Troubleshooting	0.62	0.51
Physics	0.62	0.60	Writing	0.65	0.64
Production and Processing	0.61	0.41			
Psychology	0.76	0.63			
Public Safety and Security	0.52	0.46			
Sales and Marketing	0.56	0.59			
Production and Processing	0.61	0.41			
Sociology and Anthropology	0.64	0.58			
Teaching and Course Design	0.46	0.49			
Therapy and Counseling	0.70	0.68			
Transportation	0.41	0.48			

Note. Bolded values are profile stability for each domain. Roman values are rank-order stability for each facet. The time interval was six months in Sample 2 and eight months in Sample 3.

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