



**THE OHIO STATE
UNIVERSITY**

**CENTER ON EDUCATION AND
TRAINING FOR EMPLOYMENT**

**Emphasizing Practical Learning
in Career Technical Education**

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Educators face the difficult task of keeping students motivated to learn the material at hand. Students come to class with a variety of interests and motivating factors; however, learners often share a desire to gain knowledge and skills that they can apply outside of school, as these topics feel more personally relevant. When students believe that what they are learning has utility, they are more likely to be interested—and therefore, motivated to learn ([Hulleman et al., 2017](#)). Career-technical education (CTE) students are particularly motivated by hands-on learning ([Ausburn & Brown, 2006](#)). Yet some instructors emphasize hands-on learning more than others. While past research has uncovered predictors of hands-on learning in specific circumstances (e.g., [Bulunuz, 2015](#)), many questions remain about why teachers vary in their emphasis of hands-on learning. This white paper shows how instructors may emphasize more hands-on curriculum in different stages of their career.

Hands-On Learning

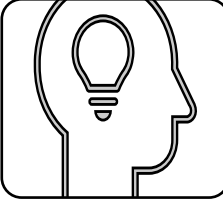

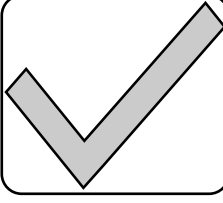
Hands-on learning is an excellent way to help learners see the utility of the curriculum. Hands-on learning is widely thought to be beneficial ([Haury & Rillero, 1994](#); [Schwichow et al., 2016](#)). In comparison to more traditional, didactic methods, hands-on learning is realistic, exciting, and motivating ([Holstermann et al., 2010](#)). For example, students in a college-level anatomy course who performed organ dissections found the activity more valuable than students who used plastic or virtual models. These students were also more likely to agree that “science is fun” than the other two groups ([Lombardi et al., 2014](#)). Conversely, teachers with negative attitudes toward science tend to use more didactic methods than hands-on activities ([Bulunuz, 2015](#)).

Despite these positive associations, hands-on learning is not necessarily more effective for improving learning outcomes ([Schwichow et al., 2016](#)). There is some evidence that hands-on learning may be more or less effective depending on the nature of the subject matter: hands-on tasks translate best to hands-on work ([Schwichow et al., 2016](#)). Hands-on learning is particularly relevant for CTE, where programs often focus on practical skills that will be relevant for specific vocations. CTE students report a preference for hands-on learning ([Ausburn & Brown, 2006](#); [Jensen & Burr, 2006](#)). Because of the positive

attitudes and possible increased effectiveness of hands-on learning in CTE, instructors may try to emphasize hands-on learning as much as possible in their courses.

Figure 1

Hands-On Learning

	<p>What is hands-on learning?</p> <ul style="list-style-type: none">•Educational experiences in which learners manipulate objects to gain knowledge/understanding•"Learning by experience" (Rutherford, 1993)
	<p>Background</p> <ul style="list-style-type: none">•Education was rote in the 19th century, with an emphasis on obedience. Later, experts encouraged learning from experiences and observation (Thorndike, 1920)•The term "hands-on" emerged in the 1960s in reference to learning how to use the computer (Rutherford, 1993)•Key to constructivist epistemologies; "people construct their own understandings of the world" (Loucks-Horsley et al., 1990)
	<p>Benefits</p> <ul style="list-style-type: none">•Learning by doing is "the best way of exciting the spirit of invention" (Piaget, 1986).•Students in activity-based science programs performed better on several outcomes compared to those in traditional classrooms. Economically or academically disadvantaged students made the largest gains (Bredderman, 1982).•Benefits of activity-centered classrooms: encourage creativity in problem solving; promote independence; help low ability students overcome challenges (Shymansky & Penick, 1981)

Adapted from [Haury & Rillero, 1994](#)

What Skills do Instructors Emphasize?

Job analysis is a method used to define the nature of jobs. It begins with a systematic procedure that divides a job into small units. After an initial set of tasks is defined, subject matter experts are often surveyed to determine which tasks are most critical to the work ([Chinn & Hertz, 2010](#)). Respondents are asked to rate each task on scales such as importance and frequency. These ratings can then be used to determine the relative emphasis of each task in curricula, assessments, and other end products. We can examine the results of job analyses to understand educators' views on the relative importance of various aspects of career technical education.

Average ratings vary across demographic groups, suggesting that the same job may be conceptualized differently by different groups. Specifically, past analyses have revealed differences by age, disability, sex, and race ([Strah & Rupp, 2022](#)). Job analysis ratings may also be influenced by raters' years of work experience ([Borman et al., 1992](#); [Dierdorff & Surface, 2007](#); [Tross & Maurer, 2000](#)). In one study, task frequency ratings tended to be higher overall for respondents with more job experience ([Tross & Maurer, 2000](#)). Task frequency ratings may also vary by experience level due to differences in which employees perform which tasks ([Borman et al., 1992](#); [Dierdorff & Surface, 2007](#)). Task importance ratings are less likely to vary based on SME characteristics, with several studies reporting no difference in average importance ratings by tenure (Borba & Spence, 2024; Dierdorff & Surface, 2007).

Our Research

In CTE, many teachers come from non-traditional backgrounds. CTE teachers often have backgrounds in industry rather than formal teacher training ([Pearson et al., 2010](#)). Alternatively-certified teachers often have considerable content knowledge because of their previous experience, and may be similarly effective compared to traditionally-certified teachers ([Stair et al., 2019](#)). This suggests that the same demographic differences may influence career-technical instruction.

While previous research has examined the influence of SME background on overall rating averages (e.g., [Tross & Maurer, 2000](#)) or individual tasks ([Borman et al., 1992](#); [Dierdorff & Surface, 2007](#)), no research has looked for a pattern of rating differences by task characteristics. We were interested in learning how CTE instructors emphasize hands-on versus hands-off content standards. Furthermore, we sought to examine differences between SMEs with more or less industry experience. We asked the following research questions:

- Will SMEs rate hands-on tasks as more important than other tasks?
- Will SMEs with more teaching experience place a stronger emphasis on hands-off tasks than SMEs with less teaching experience?
- Will SMEs with more industry experience place a stronger emphasis on hands-on tasks than SMEs with less industry experience?

Method

Data

We used preexisting survey data from a large-scale workforce development program. The program includes training in multiple career fields. The curricula for these programs are revised on a rotating basis; curricula and tests from a single career field are revised each year. Item banks are replaced approximately once every five years in accordance with NCCA standards. Career fields are structured based on a set of content standards that are shared across multiple training courses. Each training course focuses on specific content standards that are most relevant to the course description. We specifically used survey data from the health science career field. This career field contains competencies ranging from purely knowledge-based to highly hands-on.

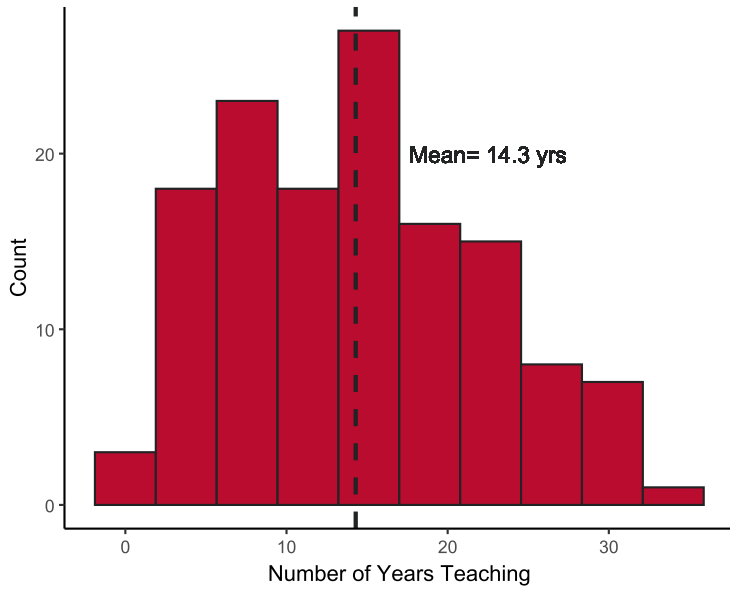
Survey

Prior to updating test blueprints, teachers completed a survey to help determine the makeup of end-of-course exams. Specifically, they rated the importance of each content standard to each course, which was used to inform blueprint calculation ([Spray & Huang, 2000](#)). Ratings ranged from “not at all important” to “extremely important” (1-5). The response distribution is presented in Figure 4.

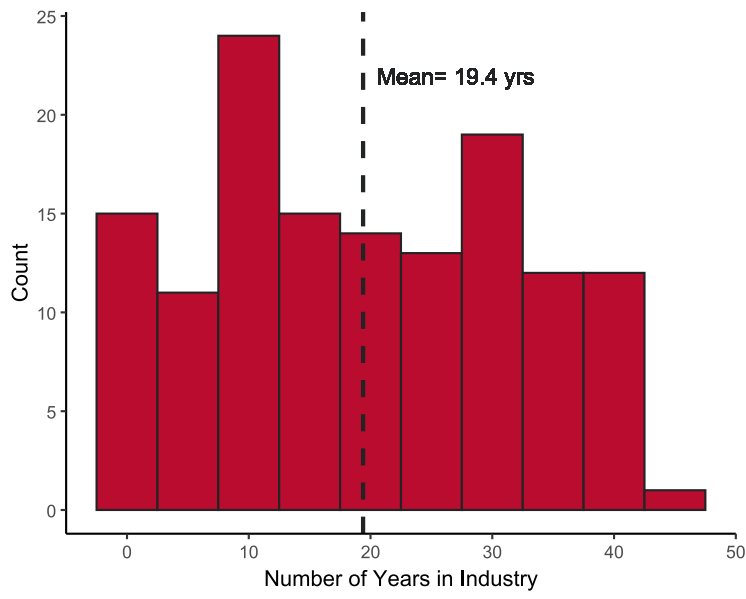
In addition to content standard ratings, the survey included an optional demographic section. Demographic questions asked SMEs to provide information about their experience in teaching and industry. We limited the analytic sample to SMEs who reported their number of years teaching and number of years working in industry. Out of the 189 SMEs who provided ratings, more than two-thirds completed these survey questions (72%). Thus, there were 136 SMEs in the final dataset. See Table 1 for SME characteristics. SMEs reported an average of 14.29 years of teaching ($SD = 8.00$) and an average of 19.39 years in industry ($SD = 12.41$; Figure 2). These values were weakly positively correlated ($r = .21, p = .01$; [Cohen, 1992](#); Figure 3).

Figure 2

Teacher demographics



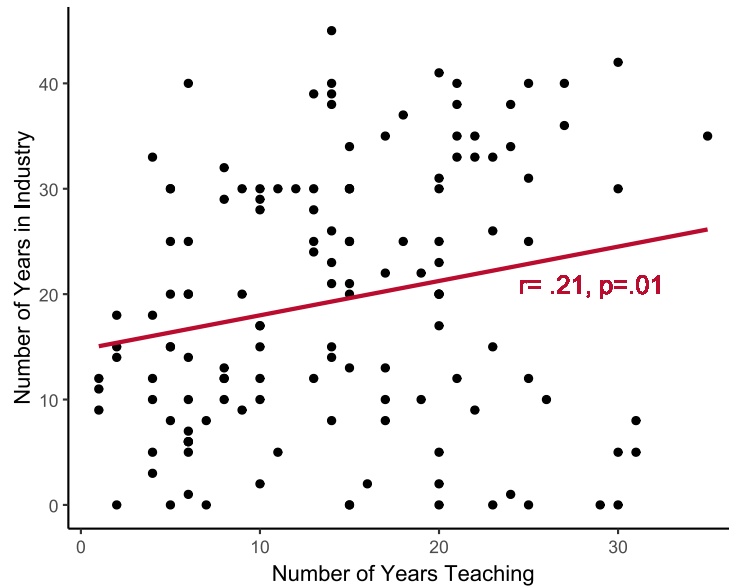
a)



b)

Figure 3

Scatterplot of years teaching by years in industry



There were a total of 5,992 individual (i.e., item-level) ratings corresponding to 32 courses. Each participant completed ratings for an average of 3.10 courses ($SD = 1.73$) and each course had between 2 and 32 content standards to rate ($M = 14.00$, $SD = 7.45$). Respondents completed between 6 and 314 ratings ($M = 113.41$, $SD = 73.89$), sometimes across multiple survey sessions.

Content standards were subdivided into individual task statements. Two of the authors rated the task statements in a binary matter as either hands-on or hands-off. Generally, the authors rated task statements as hands-off if they could be performed in a remote work setting. For example, both raters identified the task “Recognize and treat seizure” as hands-on; conversely, the task “Identify drug classifications” was determined to be hands-off.

The authors rated the 531 task statements separately, reaching a 91% agreement rate. The authors then came to a consensus on the 48 task statements where there were disagreements on the initial ratings. Finally, the authors aggregated these final ratings to characterize the degree to which each content standard was “hands-on,” using a percentage scale. If a content standard consisted of all hands-on tasks, it was assigned a *hands-on rating* value of 100%, whereas content standards made up of all hands-off tasks were given a value of 0%. About a third of content standards were determined to be entirely hands-off

(0% hands-on). Roughly ten percent of content standards had *hands-on rating* values of 100%. The remaining content standards fell between 0-100% (Figure 5).

Due to the nesting of ratings within courses and SMEs, we used cross-classified hierarchical linear modeling (CCHLM). The dependent variable was the importance rating within each model. The random effects of course and SME were included in all models tested. We first ran a null hierarchical linear model to calculate sources of variation that contributed to ratings. We found that 7.95% (intraclass correlation [ICC]= .795) of variance could be attributed to course and 13.91% (ICC= .139) could be attributed to SMEs.

In subsequent models, we tested the *hands-on rating* variable as a predictor of importance ratings. In combination with this predictor, we also tested two demographic variables: number of years teaching and number of years working in industry. We examined these demographic variables as main effects. All predictor variables were mean-centered for improved interpretability. We also tested interaction terms between *hands-on rating* and both demographic variables. Analyses were performed in RStudio 2023.12.0 using the packages *lme4* (Bates et al., 2015), *lmerTest* (Kuznetsova et al., 2017), and MuMIn (Bartoń, 2023). We compared model fit using chi-squared tests (Whittaker & Furlow, 2009) and estimated the variance explained by each model (including fixed and random effects) using conditional R^2 values (R^2c ; Bartoń, 2023).

Table 1

Subject matter expert characteristics (N = 136)

	Mean	SD	Min	Max	n
Number of Courses Rated	3.10	1.73	1	10	136
Number of Ratings	113.41	73.89	6	314	136
Years Teaching	14.29	8.00	1	35	136
Years Teaching CTE	11.01	8.03	0	31	125
Years Teaching HS	11.48	7.61	0	30	132
Years in Industry	19.39	12.41	0	45	136
Number of HS Courses Taught	6.38	5.46	0	25	128

Figure 4

Distribution of Importance Ratings

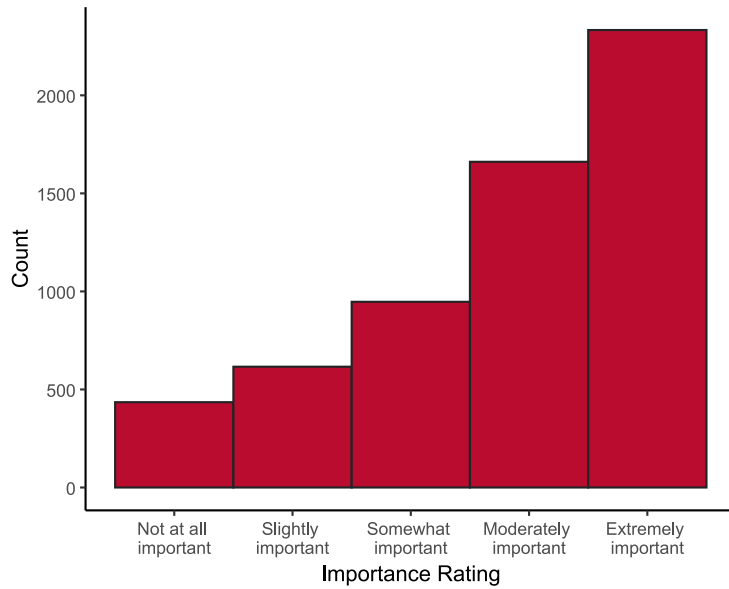
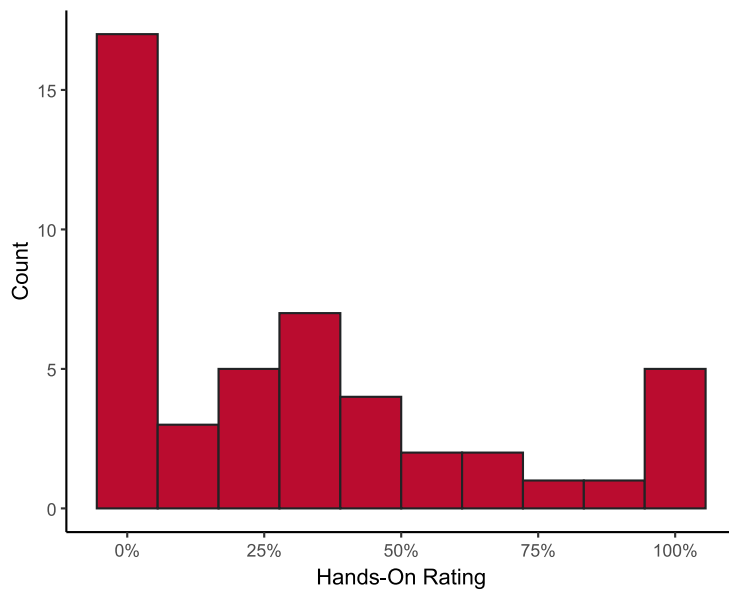


Figure 5

Hands-on rating of content standards



Results

See Table 2 for model comparison. The final model included *hands-on rating*, *number of years teaching*, and an interaction term between the two main effects (*hands-on rating * number of years teaching*). As seen in the interaction plot (Figure 6), less experienced teachers rated more hands-on

content standards as less important, more experienced teachers rated hands-on content standards as more important. The model accounted for 22.1% of variance, with the interaction effect accounting for .09% of total variance.

We repeated these analyses using the *number of years in industry* variable instead of *number of years teaching* (Table 4). In the final model, the interaction term between *hands-on rating* and *number of years in industry* was significant ($t = 2.389, p = .017$; Table 5). As shown in the interaction plot (Figure 7), hands-off content standards were rated similarly by SMEs of all levels of industry experience, but hands-on content standards were rated more highly by SMEs with more industry experience. The model accounted for 22.2% of variance, with the interaction effect accounting for .16% of total variance.

Table 2

Model Fit Statistics for Years Teaching Models

Fixed Effects	AIC	BIC	Deviance	$\chi^2(1)$	R^2c	ΔR^2c
Null model	18494	18521	18486		.219	
Hands-on rating	18496	18529	18486	0.02	.219	<.001
Hands-on rating and Years Teaching	18498	18538	18486	0.03	.220	.001
Hands-on rating, Years Teaching, and [Hands-on rating *Years Teaching]	18493	18540	18479	6.89**	.221	.001

Note. *= $p < .05$, **= $p < .01$, ***= $p < .001$. χ^2 test represents comparison between the model and the model immediately previous to it.

Table 3

Final Model: Years Teaching

Random effect	Variance	SD	
SME	.22	.47	
Course	.12	.35	
Fixed Effect	Coefficient	SE	t value
Hands-on rating	-.01	.04	-.17
Years Teaching	.00	.01	.20
Hands-on rating *Years Teaching	.01	.01	2.63

Note. SD= standard deviation, SE= standard error. The dependent variable is importance ratings.

Table 4

Model Fit Statistics for Years in Industry Models

Fixed Effects	AIC	BIC	Deviance	$\chi^2(1)$	R^2c	ΔR^2c
Null model	18494	18521	18486		.219	
Hands-on rating	18496	18529	18486	0.02	.219	<.001

Hands-on rating and Years in Industry	18496	18536	18484	1.63	.221	.002
Hands-on rating, Years in Industry, and [Hands-on rating * Years in Industry]	18493	18539	18479	5.70*	.222	.002

Note. *= $p < .05$, **= $p < .01$, ***= $p < .001$. χ^2 test represents comparison between the model and the model immediately previous to it.

Figure 6

Average importance rating by percentage of hands-on competencies per outcome and teaching experience

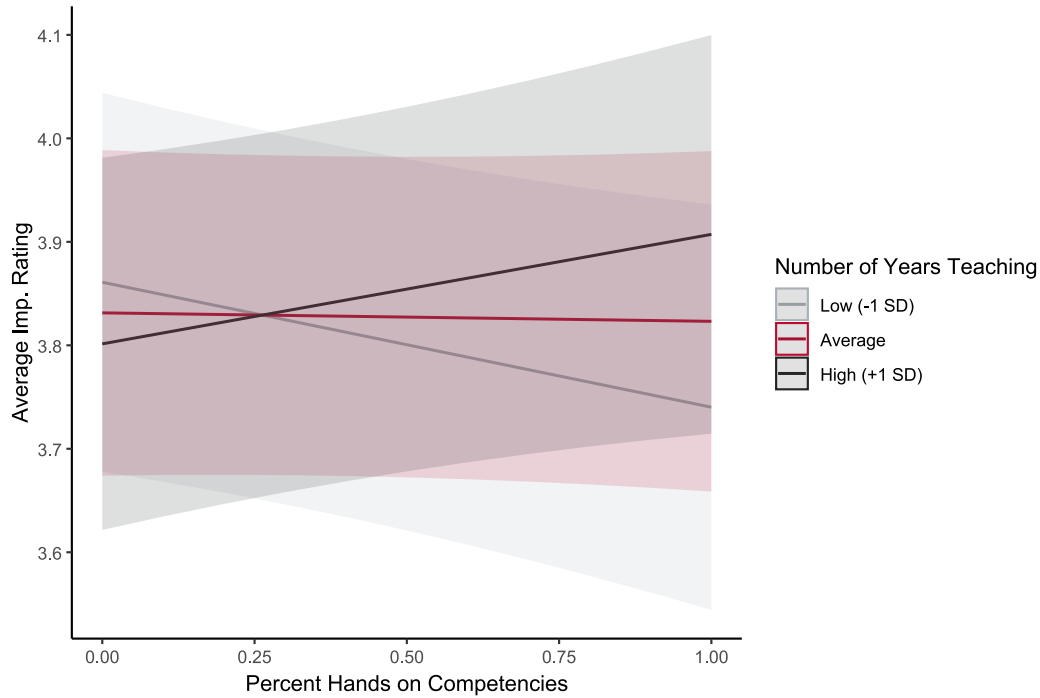


Table 5

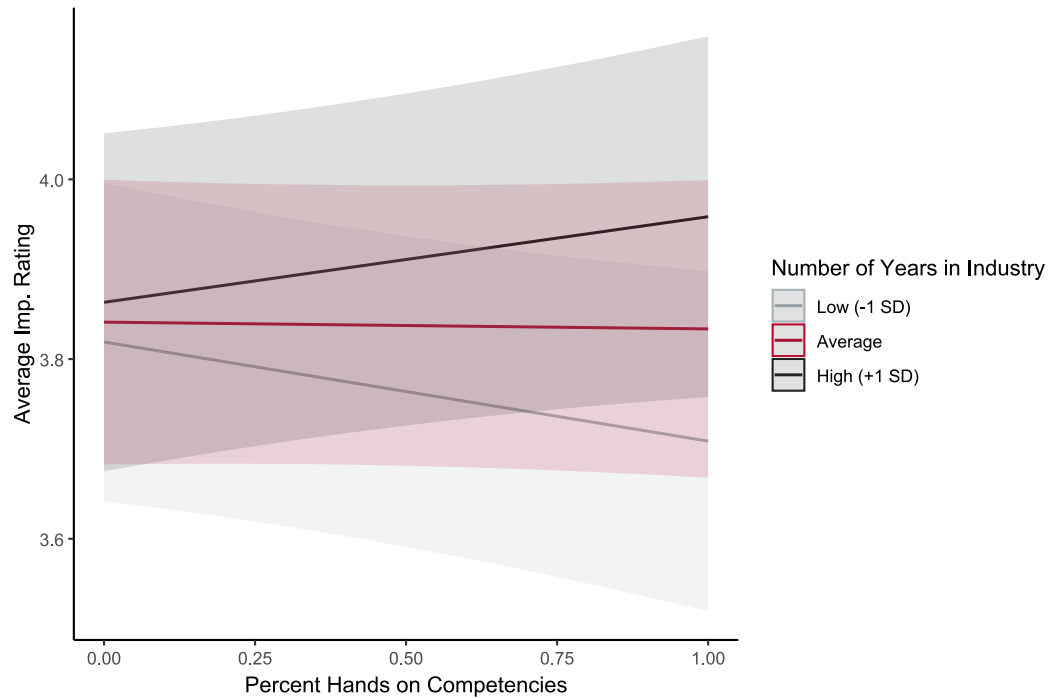
Final Model: Years in Industry

Random effect	Variance	SD	
SME	.22	.46	
Course	.13	.35	
Fixed Effect	Coefficient	SE	t value
Hands-on rating	-.01	.04	-.17
Years in Industry	.00	.00	1.29
Hands-on rating * Years in Industry	.01	.00	2.39

Note. SD= standard deviation, SE= standard error. The dependent variable is importance ratings.

Figure 7

Average importance rating by percentage of hands-on competencies per outcome and industry experience



Discussion

We conducted a series of CCHLMs to study the relationship between the hands-on nature of a content standard and the perceived importance of that content standard. While we found no relationship between our hands-on variable and importance ratings broadly, we did discover interaction effects that unveiled a more complex phenomenon. SMEs with more experience, whether it be in teaching or industry, rated more hands-on content standards as more important than their peers with less experience.

We found similar results when using years of teaching experience and years in industry to predict how important SMEs would rate more hands-on content standards. To investigate whether one demographic variable was more predictive than the other, we examined the change in R^2c associated with the interaction term in both models. The change in R^2c was slightly higher for the industry model than the teaching model (.16% vs. .09%). However, both values are very small, and the effect on average expected ratings is small, even where SMEs diverge most strongly (i.e., content standards that are 100% hands-on). When comparing SMEs with relatively minimal vs. substantial experience in industry (1 SD below average vs. 1 SD above average), the average expected importance rating for a very hands-on content

standard is approximately .3 rating points higher on a 1-5 scale for a SME with more industry experience. The effect is smaller for teaching experience, where the difference is slightly over .15 points.

Some limitations to this research restrict the generalizability of the results. First, the sample size was relatively small ($N = 136$ SMEs). Second, due to using extant data, we did not have access to information about SMEs that may have been useful for analysis. For example, we did not ask SMEs to provide their ages, which would have been a useful covariate to add to our models. Because years of experience naturally tends to correlate with age, this is a possible confound in our work that we could not control for. One alternative explanation for our findings is that older teachers value hands-on work more than younger teachers, regardless of years of experience in teaching or industry.

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