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Two discrete choice experiments on laboratory safety decisions and practices

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Abstract

Introduction: The path toward enhancing laboratory safety requires a thorough understanding of the factors that influence the safety-related decision making of laboratory personnel.

Method: We developed and administered a web-based survey to assess safety-related decision making of laboratory personnel of a government research organization. The survey included two brief discrete choice experiments (DCEs) that allowed for quantitative analysis of specific factors that potentially influence safety-related decisions and practices associated with two different hypothetical laboratory safety scenarios. One scenario related to reporting a laboratory spill, and the other scenario involved changing protective gloves between laboratory rooms. The survey also included several brief self-report measures of attitude, perception, and behavior related to safety practices.

Results: Risk perception was the most influential factor in safety-related decision making in both scenarios. Potential negative consequences and effort associated with reporting an incident and the likelihood an incident was detected by others also affected reporting likelihood. Wearing gloves was also affected somewhat by perceived exposure risk, but not by other social or work-related factors included in the scenarios.

Conclusions: The study demonstrated the promise of DCEs in quantifying the relative impact of several factors on safety-related choices of laboratory workers in two hypothetical but realistic scenarios. Participants were faced with hypothetical choice scenarios with realistic features instead of traditional scaling techniques that ask about attitudes and perceptions. The methods are suitable for addressing many occupational safety concerns in which workers face tradeoffs in their safety-related decisions and behavior.

Practical Application: Safety-related decisions regarding laboratory practices such as incident reporting and use of PPE were influenced primarily by workers' perceptions of risk of exposure and severity of risks to health and safety. This finding suggests the importance of providing laboratory workers with adequate and effective education and training on the hazards and risks associated with their work. DCEs are a promising research method for better understanding the relative influences of various personal, social, and organizational factors that shape laboratory

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safety decisions and practices. The information gained from DCEs may lead to more targeted training materials and interventions.

Keywords

Decision-making; Discrete choice experiment; Laboratory safety

1. Introduction

1.1. Background

Laboratory workers are exposed to various occupational health risks including infectious materials and cultures, radiation, toxic and flammable chemicals, and mechanical and electrical hazards (Sewell, 1995, 1996). These hazards and risks have threatened the health and safety of laboratory workers for decades. Recent safety incidents in academic, private, and government laboratory settings, such as the fires at the University of California Los Angeles (Noorden, 2011) and Texas Tech University (CSB, 2010) and the recent biosafety incidents at the Centers for Disease Control and Prevention (Weiss, 2015), reinforce prior calls to better address laboratory safety (c.f., Howard, 1986; Spencer, 1979).

Laboratory workers often face choices that pit the value of safety (e.g., wearing protective clothing to prevent exposure to a hazardous chemical) against other work pressures (e.g., getting a job done quickly to meet a deadline). Safety-related decisions made by laboratory workers involve the consideration of multiple task characteristics and setting features that are present simultaneously and often involve tradeoffs. For example, workers must often choose between receiving the value or benefits of safety and risking an adverse incident by getting the job done quickly and efficiently. Illustrating those trade-offs, Battmann and Klumb (1993) introduced a behavioral economic analysis of safety-related behavior in the workplace. In their framework, workers optimize behavioral efficiency within the limits of both internal (i.e., the skills or abilities of the worker) and external (i.e., coworkers, deadlines, or policy) constraints. In general, workers allocate behavior to maximize production and minimize effort. Violations of safety rules are conceptualized as positive trade-offs for the individual because those trade-offs increase productivity or decrease effort. Along these lines, a better understanding of workers' preferences (i.e., perceptions) regarding safety-related benefit-risk tradeoffs may lead to more effective injury-prevention strategies.

1.2. Decision-making research

The study of human decision-making has a long history in many scientific disciplines such as experimental economics, behavioral economics, and behavior analysis. Overlapping interests across these fields have produced many theories and a wealth of empirical data, and the findings have informed policy and intervention development in finance, healthcare, and government (Thaler & Sunstein, 2009). One specific area of decision-making research that has been particularly fruitful is the analysis of human choice and preference for understanding the factors that underlie many different types of behavioral phenomena. For example, in a study of consumer healthcare preferences, Van Houtven, Johnson, Kilambi, and Hauber (2011) noted that health-related decisions, such as those related to medical treatments, often involve choices between the potential for health benefits and the "countervailing risk of a serious adverse health outcome or even death" (p. 469). Understanding how and why people make particular decisions has the potential to improve welfare on a societal and individual level.

Various research approaches for assessing preferences can be categorized into two types of experiments: *revealed preference* and *stated preference*. Revealed preference experiments refer to studies of actual choices that have been made and recorded. Surveillance or observed behavioral data are common sources of data on actual choices made by individuals or groups (Louviere, Hensher, & Swait, 2000b). Evanoff et al. (1999) provides a good example of a revealed-preference study in occupational safety. In this study, video recordings and observational data on the frequency of occurrences in which personal protective equipment (PPE) was not used were analyzed to assess changes in PPE compliance in emergency room physicians after educational interventions were implemented. That is, the data *revealed preferences* among the physicians in using PPE. Other examples of revealed preferences include direct observation of specific laboratory behaviors, such as handwashing, glove use, and hand-to-face contact (e.g., Johnston, Eggett, Johnson, & Reading, 2014; Johnston, Merrill, Zimmerman, Collingwood, & Reading, 2016).

Revealed-preference methods can provide accurate snapshots of choices that have occurred in a given setting because the methods assess actual behavior (as opposed to hypothetical or self-reported behavior). However, revealed preference methods have several drawbacks (Louviere et al., 2000b). One common weakness of revealed preference methods is that new products, services, or conditions that do not exist or are not yet available cannot be evaluated. For example, you cannot use revealed preference techniques to determine the desirability of anti-gravity fall protection. Another weakness is that revealed preference techniques are not useful when there may be limited choices available to individuals in a given context. For example, sometimes workers must use a company-issued style or brand of protective clothing that they would otherwise not choose if given the opportunity. There are also practical limitations to using revealed preference techniques. Collecting observational data may be too cumbersome or effortful (Louviere et al., 2000b), and workplaces may not have the time, money, or staff required to observe and collect data on PPE use, accident reporting, compliance with safety protocols, or other safety-related behaviors.

Stated preference, on the other hand, refers to survey procedures that assess the choices that individuals report they would make given a set of specific hypothetical conditions (Adamowicz, Louviere, & Williams, 1994). Some of the limitations of revealed-preference methods can be overcome with stated-preference methods. For example, researchers can assess scenarios not currently available or not yet implemented. Compared with the arduous task of collecting observational data in a revealed-preference study, stated-preference studies are relatively easy to conduct. Typically, administering a short survey or set of surveys to the relevant sample population can reduce the burden on the data collector.

There are several types of stated-preference methods. In occupational safety research, it is common to use *non-comparative* scaling techniques in which subjects are asked to assess a set of items and assign a rating to each item independently. An example of a non-comparative survey question would ask workers to rate their agreement with the statement "I feel free to report safety violations where I work" on a 4-point scale from "*strongly agree*" to "*strongly disagree*" (Hahn & Murphy, 2008). These types of survey questions are ubiquitous in safety surveys that assess workers perceptions, judgments, beliefs, or attitudes about safety concerns (Colla, Bracken, Kinney, & Weeks, 2005). The advantages of non-comparative scaling techniques include that they are commonly used and are therefore familiar and easily understood by respondents, the results are quantifiable, and the respondent can express neutrality or indecision (Hasson & Arnetz, 2005). The disadvantages of non-comparative scaling techniques include the possibility for systematic response errors including a reluctance to respond on the extreme ends of the scale (i.e., central tendency error) as well as the confounding effects of direction (e.g., agree/disagree) and intensity (e.g., strongly agree or strongly disagree) of choice ratings (Albaum, 1997).

Comparative-scaling techniques are an alternative approach in which individuals evaluate two or more items simultaneously. Common comparative-scaling examples, such as paired comparisons, rank ordering, and Q-sort, have advantages. For instance, comparative techniques mirror real-life decision making more closely than non-comparative methods because individuals typically do not evaluate a single item or characteristic alone or in isolation of other factors. Instead, choices are based on subjective, evaluations of many different items or characteristics that are present simultaneously. Comparative-scaling questions also can result in a list of preferences, from most to least preferred, in contrast to noncomparative-scaling techniques in which respondents can select "*Strongly Agree*" for all options, making it difficult to derive an order of preference.

1.3. Discrete choice experiment

A discrete choice experiment (DCE) is a sophisticated type of comparative scaling method that has been developed by economists (e.g. McFadden, 1974). It has been defined as a "general preference elicitation approach that asks agents to make choice(s) between two or more discrete alternatives where at least one attribute of the alternative is systematically varied across responses in such a way that information related to preference parameters of an indirect utility function can be inferred" (Carson & Louviere, 2011, p. 543). The goal of a DCE is to determine the overall value or importance of a characteristic (or set of characteristics) based on how respondents make choices in hypothetical scenarios that involved those characteristics. The methods for conducting and analyzing DCEs to better understand decision making have spread to domains beyond economics, including marketing (Kristallis, Linardakis, & Mamalis, 2010), transportation (Langbroek, Franklin, & Susilo, 2016), tourism (Crouch & Louviere, 2001), environmental valuation (Hoyos, 2010), and healthcare (Lawyer, Schoepflin, Green, & Jenks, 2011).

In a typical DCE, a participant chooses between two or more alternatives that differ on one or more characteristics. These characteristics are termed *attributes*. For example, in a study to assess consumer preferences for cell phones, the attributes might be screen size, battery size, brand, and cost. Each attribute also consists of several *levels*. Extending the previous example, the levels for screen size might be 16.5 cm and 14 cm; the brands might be Apple and Samsung; and the levels for cost might be $300, $600, and $900. The DCE survey is constructed by arranging multiple *choice sets* with two or more choice alternatives from which the participant selects an alternative. Across multiple choice sets, the attribute levels are systematically manipulated so that the researcher can determine how the various combinations of attribute levels affect the likelihood of selecting a choice alternative.

The theoretical foundation for DCEs is rooted in the *random utility theory* of choice behavior (Thurstone, 1927). The assumption of random utility theory, as applied to DCEs, is that each choice alternative being considered has a latent utility, and the choice alternative with the greatest utility to the participant will be chosen (Louviere, Flynn, & Carson, 2010). As a latent construct, utility is not directly observable, but it can be derived from analyzing the pattern of choices made in a DCE. That is, choice sets that are selected more often are assumed to have a greater utility than choice sets that are selected less frequently. As described in the preceding paragraph, the researcher systematically varies the attribute levels of the choice alternatives to determine the utility gained (or lost) by each attribute level. The basic axiom of random utility theory is:

$$U_{ni} = V_{ni} + \epsilon_{ni} \qquad (1)$$

where U_{ni} is the latent, unobservable utility that individual n associates with choice alternative i, V_{ni} is the systematic, explainable component of utility, and ϵ_{ni} is the random component. The systematic component consists of the attributes and levels of the alternatives as well as characteristics of the individual (if included). The random component consists of all the unidentified factors that affect choices (i.e., model error). With random utility theory, the probability that individual n will choose alternative i instead of alternative j is represented by:

$$\begin{aligned} P_{ni} &= \text{Prob}\left(U_{ni} > U_{nj}, \forall j \neq i\right) \\ P_{ni} &= \text{Prob}\left(V_{ni} + \epsilon_{ni} > V_{nj} + \epsilon_{nj}, \forall j \neq i\right) \\ P_{ni} &= \text{Prob}\left(V_{ni} - V_{nj} > \epsilon_{nj} - \epsilon_{ni}, \forall j \neq i\right. \end{aligned} \qquad (2)$$

where alternative i does not have the same properties as alternative j. That is, the likelihood of selecting alternative i is based on the difference in the systematic component of the utilities of the two alternatives after accounting for the random component of the utilities. The systematic component can be calculated on the basis of how choice patterns change across the manipulations of the attributes and levels using advanced logit or probit models (Louviere, Hensher, & Swait, 2000a). That is, the models estimate the various systematic utilities based on the obtained choice probabilities.

1.4. Study objectives

Despite the apparent relevance of methods for analyzing human choice in occupational settings, the theoretical and analytical concepts of choice-based research methods have not yet found their way into mainstream occupational safety research. This void provides the main impetus for the proposed project—to demonstrate and evaluate the utility of DCEs for studying decision making in occupational safety. We chose laboratory safety as the context to provide two different examples of DCEs.

The topic of laboratory safety provides many good scenarios to illustrate the potential of DCEs to evaluate the various personal, social, and organizational factors that may influence the decision making of laboratory workers. For example, underreporting of safety incidents is frequently cited as a laboratory safety concern (e.g., CDC, 1997; Voide, et al., 2012). Reasons for underreporting include fear of discipline, reprisal, and job loss. There also may be institutional barriers to reporting, such as when organizations establish zero-rate injury goals or implement incentive programs that reward low levels of injury reporting (GAO, 2009; Lipscomb, Nolan, Patterson, Sticca, & Myers, 2013; Pransky, Snyder, Dembe, & Himmelstein, 1999). In laboratory settings, specifically, the underreporting of laboratory infections was widely acknowledged to be due to fear of reprisal and stigma associated with such events (Sewell, 1995).

Another common laboratory safety concern is proper use of PPE when working with hazardous or infectious agents. For example, in a recent survey approximately 66–87% of lab workers in academic, government, and industry settings reported that they did not wear lab coats even though it was required in their workplace (Schröder, Huang, Ellis, Gibson, & Wayne, 2016). Studies have revealed several potentially important factors that serve as either facilitators or barriers to proper PPE use. For example, behavioral modeling by supervisors and coworkers had the strongest association with workers' compliance with handwashing and glove removal practices. Additionally, workers in laboratories with written handwashing policies had higher compliance than those with no policy (Johnston et al., 2016). In a survey of Canadian clinical laboratory workers, 62% of respondents reported that they did not consistently wear gloves while handling blood and blood products. The reasons cited for not using PPE included "the risk of infection is small without gloves" and "gloves interfere with my job skills" (Main, Carusone, Davis, & Loeb, 2008). In another study of biosafety level-2 (BSL-2) workers, workers' risk perceptions had a modest relation to the frequency of hand-to-face contact behaviors (Johnston et al., 2014).

Using laboratory safety as the context, we designed and conducted two DCEs to assess how the various personal, social, and organizational factors affect the likelihood of reporting a safety incident and the likelihood of wearing PPE within a population of laboratory workers. A secondary goal was to demonstrate for safety researchers and professionals the methods and of interpretation of DCEs. To the best of our knowledge, this is the first DCE study to address laboratory safety decision making.

2. Methods

2.1. Participants

A total of 123 employees of various agencies of the Centers for Disease Control and Prevention (CDC), a U.S. government public health research agency, completed the survey. Individuals were excluded from the survey if they were not full-time equivalent employees (e.g., students, contractors, temporary workers) or did not work in a laboratory setting. The Institutional Review Board of the National Institute for Occupational Safety and Health, which is part of CDC, reviewed the survey protocol and determined it to be exempt as no personal identifiable information was being collected.

2.2. The survey instrument

The survey was hosted and managed by Qualtrics (Provo, UT). Respondents accessed the survey by clicking on a web link. To encourage candor, the survey did not collect personal or identifying information about survey respondents. The survey consisted of 87 questions and required approximately 25 min to complete. The first two questions screened the respondent's eligibility. If a respondent did not meet the eligibility criteria, the following message appeared, and the respondent was prevented from taking the rest of the survey: "Thank you for taking time to respond to this survey; however, only full-time equivalent employees or fellows are eligible to participate." Eligible respondents then completed a question to determine their work history. The remainder of the survey consisted of nine sections presented across two blocks. In the first block, respondents completed two DCEs. In the second block, respondents completed the remaining subscales. The sequence of the DCEs and subscales in each block was determined by a randomization function in Qualtrics. The final subscale was a safety climate survey. A description of each section and subscale follows below.

2.2.1. Discrete choice experiments—Two brief DCEs, each with eight questions, assessed safety-related decision making in two different hypothetical scenarios. The DCEs were developed in accordance with the well-accepted recommendations for developing a DCE (Bridges et al., 2011; Johnson et al., 2013). We reviewed the laboratory safety literature, held discussions with laboratory safety experts, and conducted qualitative interviews with a small sample of laboratory workers to reveal salient and high priority laboratory safety challenges experienced across different laboratory settings. From this information, we selected two topics for study in the DCEs. The first DCE (hereafter, Reporting DCE) assessed factors associated with decisions to report a safety incident. The second DCE (hereafter, PPE DCE) assessed the factors associated with decisions to comply with a PPE policy that requires workers to remove and replace gloves when moving between different laboratory spaces. Like the selection of scenarios, the attributes and attribute levels for each scenario were selected based on a review of the extant safety literature, discussions with laboratory safety experts, and interviews with laboratory workers.

Table 1 shows a list of attributes and attribute levels included in the DCEs. For each attributed listed there exists empirical support linking it with safety performance. Risk perception is one factor that has been linked repeatedly to laboratory safety performance (e.g., Johnston et al., 2014; Schröder et al., 2016). For example, in recent survey of academic, government, and industry laboratories, workers' compliance with PPE policies was strongly correlated with their risk perception (Schröder et al., 2016). Another important factor is lab supervisors leadership style and whether they use a positive reward system (Schröder et al., 2016). Social and peer influences are additional factors that may influence safety decisions and behavior. For instance, in a study of observational learning, participants who engaged in a computer task during noisy conditions were more likely to don hearing protection when other participants around them (study confederates) also wore hearing protection (Olson, Grosshuesch, Schmidt, Gray, & Wipfli, 2009). Furthermore, a common theme revealed by several lab safety studies is the concern that safety rules and policies may place undue burdens on workers. For example, in a recent survey, 30–37% of workers in government laboratories reported that safety rules negatively affected their productivity and interfered with their scientific discovery process (Schröder et al., 2016). Undoubtedly, many other individual factors may be identified from the current safety literature; however, the listed attributes and levels were also identified as important through interviews with the relevant safety experts.

The choice sets for each DCE were constructed using the Choice Design tool in JMP (Version 12; Cary, NC), which yielded a fractional-factorial design in which only a subset of all possible combination of attributes and levels (up to 80) were included in the design. This design kept the number of choice sets required to a minimum while also ensuring a balanced and efficient design. The final number of choice sets in each DCE was 16; these were further divided into Version A and Version B with eight choice sets each. The version each respondent completed was randomly assigned via the Qualtrics randomization function with counter-balancing across successive participants.

Fig. 1 shows examples of the first choice set in each DCE. In the Reporting DCE, respondents were instructed to imagine that a splash or spill occurred in the laboratory while working with a hazardous agent, and then click on either the left or right box showing the scenario in which they would be more likely to report the event as a safety incident. In the PPE DCE, respondents were instructed to imagine that they are working in a lab in which potentially hazardous agents are used, and they need to walk from the current lab space to a different lab space through a corridor and a closed door. Respondents were further prompted to assume that there was a policy requiring them to remove and replace their gloves when moving between the different lab spaces. (Indeed, this was a current policy in effect.) They were then instructed to click on either the left or the right scenario in which they would be more likely to remove and replace the gloves. Clicking on either box turned that box color to red to indicate that a selection was made and recorded. After completing the first choice set, the seven remaining choice sets appeared in a similar manner, except that they included choice alternatives with different attribute levels.

2.2.2. Other survey items and subscales—Several other questions and subscales were included in the survey. To encourage participation and allay any concerns about anonymity, the survey solicited no demographics and limited job-related information. Two questions solicited information about the respondents' exposure to specific hazards and risks. One question asked respondents to indicate the biosafety level (e.g., BSL 1–4) in which they worked. A second question asked respondents to indicate the nature of the hazards (e.g., biological, chemical, radioactive, physical, animals, etc.) they handled. Additional measures of various psychosocial constructs were also included to explore other research questions that are beyond the scope of the present article. Nevertheless, these additional constructs are described here along with some preliminary results.

Eight questions provided various measures of safety-related performance in the past year, such as incident reporting behaviors and safety committee experience, and safety-related outcomes, such as injury and near miss experience. Multiple-choice questions asked for the following: (1) number of work-related injuries; (2) number of near misses experienced; (3) number of safety incidents experience but not reported; (4) number of safety incidents witnessed but not reported; (5) total number of safety incidents reported by the respondent; (6) number of times the respondent deviated from safety-related standard operating procedures; and (7) whether the respondent served or had been asked to serve on a safety committee or safety audit team. Some questions were adapted from (Hayes, Perander, Smecko, & Trask, 1998) to serve collectively as measures of safety-related behavior and outcomes.

To assess the role of job characteristics in safety-related decisions, the construct of Job Routineness was assessed with a five-question scale adapted from previous research (Hage & Aiken, 1969; Price, 1972). For example, one question asked respondents to rate the following statement: “People in my lab do the same job in the same way every day.” Response options varied between *definitely true* to *definitely false* on a Likert scale. Higher scores indicated greater variability in job tasks. This scale was included based on evidence that Job Routineness moderates the relation between safety climate and safety behavior (Zohar & Luria, 2005).

Two questions assessed general safety-related knowledge and skills related to the workers’ familiarity with the policies and procedures for reporting a safety incident and for completing the tasks associated with their jobs. Two additional questions assessed how well they have been informed of safety hazards and risks and how well they have been trained to perform their jobs safety. Each question appeared as a 7-point Likert scale with anchors of *Strongly Disagree* = 1 and *Strongly Agree* = 7. Responses to each question were summed; higher scores indicated greater safety-related knowledge and skills.

Eight questions were brief delayed reward discounting (DRD) task questions (Gray, Amlung, Acker, Sweet, & MacKillop, 2014). For example, the first question asked, “Would you rather have $50 today or $100 in 1 year?” The second question asked, “Would you rather have $70 today or $100 in 1 month?” The dollar amounts and delays varied further in remaining questions. The DRD can be used to predict the extent to which individuals discount behavioral outcomes (e.g., monetary rewards) when those outcomes are delayed. For each question, choosing the delayed alternative has a unique (or weighted) effect on the predicted area under the curve (AUC; Myerson, Green, & Warusawitharana, 2001), which is a measure of discounting. Lower values of AUC indicate more discounting of delayed rewards (i.e., impulsivity). For example, in the first question, choosing $100 in 1 year in the first question increases the predicted AUC by 0.172 and in the second question, choosing $100 in 1 month increases the predicted AUC by 0.104. Thus, an overall predicted AUC value was derived by taking the sum of the unique contributions to the predicted AUC for each question in which a participant selected the delayed monetary reward (i.e., AUC = weighted sum of choices for the delayed outcome).

The consideration of future safety consequences (CFSC) scale (Probst, Graso, Estrada, & Greer, 2013) was included to provide a measure of short-term versus long-term safety outcomes. The scale included six questions about reporting injuries and incidents as well as following appropriate safety procedures. Example questions included “Even though it sometimes takes longer, it is better in the long run to follow appropriate safety procedures” and “Failure to immediately report a workplace injury might result in serious problems later." Each question appeared as a 7-point Likert scale with anchors of *Strongly Disagree* = 1 and *Strongly Agree* = 7. Scores on each question were coded so that higher scores indicated greater sensitivity to future safety consequences.

Four questions assessed the frequency of respondents' perceived receipt of positive and negative feedback from their supervisors for safety-related behavior and productivity. For example, one question asked, "How often do you receive positive feedback (e.g., praise or information) for safety-related activities?" Another question asked, "How often do you receive negative feedback (e.g., praise or information) for safety-related activities." Each question appeared as a 5-point Likert scale with anchors of *Never* = 1 and *Always* = 5. Questions about negative feedback were reverse coded, and the responses from each question were summed to calculate a total feedback score. Higher scores indicated a higher frequency of positive feedback.

Safety climate (SC) was assessed using a well validated scale (Zohar & Luria, 2005), which yields a measure of climate level for both upper and supervisor levels of management. A total of 32 questions (16 questions relating to upper management and 16 questions relating to supervisors) appeared as a 5-point Likert scales with anchors of *Completely Disagree* = 1 and *Completely Agree* = 5. Scores from the questions were summed to yield the SC level for supervisors and management. Higher scores indicated a more positive safety climate level.

2.3. Survey administration

Email announcements of the survey were sent to laboratory workers by managers or supervisors of laboratory-based divisions, branches, and teams across the organization. These emails provided a brief description of the survey, eligibility requirements, and a web link to the survey. To encourage participation, at least two additional emails were sent during the survey enrollment period to serve as reminders and a brief announcement was published in the agency's safety newsletter. The survey enrollment period started in April 2018 and lasted approximately 12 weeks.

2.4. Data analysis

Sample characteristics and responses to selected survey items that pertained to safety experiences and reporting behaviors were described with descriptive statistics and measures of central tendency. Because some survey measures ordinal variables, bivariate Spearman correlations also were computed to explore relations among the variables.

The results for DCEs were analyzed using a multinomial logit model with Nlogit 5 (Econometric Software, Inc., Plainview, NY). The resulting multinomial logit analysis yielded a set of beta coefficients that indicate the extent to which the specific level of an attribute increases or decreases the utility of a choice alternative that includes that attribute level relative to the reference levels. Because the absolute values of beta coefficients in a multinomial logit model for DCEs cannot be compared meaningful to each other (Hauber et al., 2016), a probability analysis (cf. Lancsar, Louviere, & Flynn, 2007) was also conducted. This analysis yields the probability of choosing an alternative with a specific attribute level relative to the average distribution of choices (i.e., marginal probabilities). The marginal probabilities show the average effect of each attribute level on choice isolated from the effects of the other attribute levels. For example, a −10% marginal probability for No Injury Risk in the Reporting DCE means that a person, who perceives no risk after a spill, is 10% less likely to report the spill, all else being equal. The marginal probabilities make it possible to rank the relative impact or importance of each attribute level across all attributes and levels. The marginal probabilities were calculated for each attribute level in each DCE.

3. Results

3.1. Respondent characteristics and safety experiences

Table 2 shows several notable characteristics of the respondents, including responses to survey questions pertaining to employment type, years of experience, and injury experience. The sample consisted of laboratory workers with a wide range of experience, and approximately half of the sample reported working with hazards consistent with BSL 2 or higher. Nearly half of the sample included individuals who reported prior experience serving on a safety committee, safety council, or safety audit or review team.

A small but appreciable percentage of respondents (5%) indicated experiencing a work-related injury in the previous year, and a larger percentage of respondents (~22%) indicated experiencing a “near miss” safety incident within the previous year. A lower percentage of respondents (16%) indicated that they reported one or more safety incidents, defined as either a major or a minor safety event in the previous year; whereas only about 5% indicated that they experienced an incident but did not report it. Almost 10% of the respondents indicated witnessing a safety incident but did not report it. About 16% of the respondents admitted to deviating from safety-related standard operating procedures in the previous year.

For each respondent, a total score was calculated for each of various subscales in the survey (e.g., job routineness, safety knowledge and skills, CFSC, positive and negative feedback, and safety climate). These scores were included in additional analyses to identify relations among the key factors and constructs. Table 3 shows the descriptive statistics from the scores obtained on the subscales. Most (but not all) respondents reported being well aware of hazards and risks, well informed of safety policies/procedures, and well trained to perform their jobs safely. On the safety-related knowledge and skills scale, 88% of respondents reported being very well informed or extremely well informed of the safety hazards and risks associated with their jobs. Ninety percent of respondents reported being very well trained or extremely well trained to perform the skills necessary to do their jobs safely.

Perceptions of safety climate were generally positive for both supervisor and upper management, and mean SC scores for both supervisors and upper management were not appreciably different. Although there were individual exceptions, the majority of respondents reported positive or favorable perceptions of supervisors and management across the various safety climate questions.

Table 4 displays the Spearman’s correlations for each pairwise combination of the scales included in the survey.

3.2. Discrete choice experiments

Table 5 shows the results of the multinomial logit analysis for the reporting DCE, which assessed the decision to report a laboratory spill. Preliminary analyses revealed a statistically significant constant parameter indicating a position bias (i.e., selecting the left choice alternative frequently) that co-varied with two demographic variables (years of experience and safety committee experience). To attempt to control for this bias in responding, we included the covariates as parameters in the model. The final model revealed that all four attributes (i.e., injury risk, detection likelihood, reporting effort, and reporting outcome) were found to significantly influence respondents' decisions to report the spill. Scenarios that depicted critical or serious injury risk were associated with increased utility for reporting the incident ($\beta = 2.79$, $p < 0.0001$ and $\beta = 1.81$, $p < 0.0001$, respectively). The other significant but less influential factors were when reporting the incident might result in a negative outcome ($\beta = -0.85$, $p < 0.0001$), when there was moderate effort associated with reporting the incident ($\beta = -0.47$, $p = 0.0092$), and when detection (of the spill) by others was likely ($\beta = 0.32$, $p = 0.0358$). The coefficients for moderate effort and negative outcome were negative, indicating that respondents were less likely to report the spill in the scenarios with those attribute levels.

Fig. 2 displays the marginal probabilities of each attribute on the decision to report a spill. Perceptions of no risk had the most impact on decisions to report the spill, decreasing the probability of reporting the spill by 30.9%, followed by perceptions of critical and serious risks, which increased the probability of reporting the spill by 11% and 1%, respectively. A perceived positive outcome of reporting the spill increased the probability of reporting the incident by 5.7%, whereas a perceived negative outcome of reporting the spill decreased the probability of reporting the incident 5.3%. When the scenario was associated with moderate effort, the probability of reporting the spill decreased by 4.7%. When detection of the spill by other people was either likely or unlikely, the decision to report the spill either increased or decreased, respectively, by approximately 2% in both cases.

Table 6 shows the results of the multinomial logit analysis of the PPE DCE, which assessed the decision to remove and replace protective gloves according the PPE policy described in the scenario. Among the five attributes that were tested in the hypothetical scenarios, injury risk and exposure risk significantly influenced decisions to remove and replace gloves. Choice alternatives that depicted a critical risk or serious risk (to injury) influenced wearing of gloves the most ($\beta = 2.91$, $p < 0.0001$ and $\beta = 2.22$, $p < 0.0001$, respectively), followed by choice alternatives in which there was some exposure ($\beta = 1.46$, $p < 0.0001$).

Fig. 3 displays the marginal probabilities of each attribute on the decision to comply with a PPE policy. Perceptions of critical risk had the most impact on decisions to comply with PPE policy as described in the scenario, increasing the probability of removing and replacing protective gloves in the scenario by 26.1%, followed by perceptions of serious risk, which increased the probability of removing and replacing protective gloves by 20.8%. The probability of removing and replacing protective gloves decreased by 15.1% when there was little or no exposure risk, whereas probability of removing and replacing protective gloves increased by 7.8% when there was some exposure risk. The probability of removing and replacing protective gloves decreased 1.9% and 1.7% when the scenario, respectively, was associated with working alone and when compliance with the PPE policy was an uncommon practice in the laboratory. A potential disruption to workflow had no appreciable impact on the probability of removing and replacing protective gloves (<2% change).

4. Discussion

4.1. General findings

Using the framework and methods of a DCE, we found that severity of a potential injury was the most influential factor in safety-related decision making in this sample of laboratory workers. Across the two separate hypothetical scenarios depicted in the DCEs, the possibility of critical and serious risk of injury increased the likelihood of either reporting an incident or the likelihood of properly using protective gloves. The findings confirm the results of other studies showing associations between risk perception and laboratory safety practices (Johnston et al., 2014; Schröder et al., 2016; Taylor & Snyder, 2017). For instance, laboratory workers' tendency to touch their faces while engaged in a task was negatively correlated with their perception of increased infection risk (Johnston et al., 2014). This finding is encouraging because safety behavior should be motivated ideally by the presence of hazards and risks and less by secondary factors such as arbitrary rules or social pressures. Yet despite the apparent importance of risk perception, a recent survey found that only about 50% of lab workers adopt and use formal risk assessment procedures suggesting that workers' personal risk perception may not always be accurate (Schröder et al., 2016).

Furthermore, individuals' assessment of risk perception has been shown to be conditional on their engaging (or failing to engage) in behaviors such as adhering to specific safety procedures (Taylor & Snyder, 2017). For example, a lab worker handling a potentially lethal chemical might perceive their risk very low because their assessment of risk includes their intention to comply with all applicable safety procedures (e.g., proper chemical storage, handling, and disposal, and use of effective personal protective technology). Thus, researchers have cautioned that assessments of risk perception, which do not take into account its conditional status with specific safety behaviors, are difficult to interpret (Taylor & Snyder, 2017). In the present study, we showed that DCEs effectively address this concern by evaluating the influence of risk perception in the context of realistic scenarios in which the behaviors and potential influencing factors are specified.

The present findings also revealed that factors relating to work and social pressures exerted some influence over safety-related decision making in the DCE scenarios. For instance, the likelihood of reporting a safety incident decreased somewhat when there was a potential negative consequence of reporting the incident or when reporting the incident required some effort. The likelihood of reporting a safety incident in the scenarios was also increased when there was a likelihood of the incident being detected by others. This finding is consistent with studies on ethical decision-making showing importance of perceived social consequences. For example, studies show that work-related ethical behavior such as *not* falsifying payroll time sheets, improperly accepting gifts from a sales agent, or improperly copying company-owned software, increased when the chance of getting caught was high (Callanan, Rotenberry, Perri, & Oehlers, 2010).

In scenarios involving the proper wearing and removal of gloves, the severity of a potential injury and perceived exposure risk were the main influencers of safety decisions. There was no significant influence of other social or work-related factors. For instance, decisions to properly use the gloves was not influenced significantly when other workers were present, when wearing/removal of gloves was a common or uncommon lab practice, or when wearing of gloves was disruptive to workflow. It is not clear why social and work-related factors only influenced incident-reporting decisions in the Reporting DCE and not proper glove compliance decisions in the PPE DCE. However, it is tempting to speculate that decisions to use PPE may be less susceptible to pressures from extraneous variables because it more directly ensures personal safety, whereas reporting an incident may be perceived to satisfy mainly organizational policy requirements. A future DCE study could examine questions related to personal risk assessment versus specific organizational rule requirements in greater depth.

4.2. Study limitations

As with similar survey studies of this type, there were several limitations. For instance, the sample size was small and thus it may not be possible to generalize the findings beyond this study's sample. Possible reasons for the low response rate can attributed to indirect survey distribution method and advertising of the survey within the organization. In addition, the survey was administered around the same time as an agency-wide employment satisfaction survey and, thus, survey fatigue may have contributed to the low response. Nevertheless, the sample size was deemed sufficiently large for achieving the stated objective of demonstrating the use of DCEs to evaluate multiple factors associated with laboratory workers' safety-related decision-making.

Another limitation was that we collected limited demographics and few potentially relevant details about the type of laboratory work and associated hazards faced by each respondent. To safe-guard respondents' anonymity, the survey purposively asked few questions about work location or other employment conditions, and thus we were not able to identify or study potentially important differences in safety-related perceptions and decision making across different job types or work locations. It would have been informative to compare injuries, near misses, perceptions, and decision-making by job type and other important demographic and job-related variables. Indeed, research has shown differences in laboratory injury rates across different job titles. For example, in a study of academic research laboratories, rates of injuries among student employees, animal caretakers, and graduate assistants were higher than professors, lab technicians, research associates, and veterinary technicians (Simmons, Matos, & Simpson, 2017). Furthermore, we also found a position bias (selecting the left choice alternative frequently), which co-varied with two demographic variables (years of experience and safety committee experience). This might be accounted for by the presence of a dominant alternative in the design, and it is possible that the dominant alternative interacted with those covariates. More pilot testing of various choice designs during the development phase might have yielded a more balanced design; however, a future study that specifically examined that the influence of these factors on choice is warranted.

Another noteworthy limitation was that nearly one-half of the respondents reported having served on a safety committee or audit in the past making them more likely to have an interest in safety issues or comply with safety policies. Perceptions of safety climate were also generally positive in relation to both supervisor and upper levels of management, and most (but not all) respondents reported being well aware of hazards and risks, well informed of safety policies/procedures, and well trained to perform their jobs safely. In the present study, less than 5% of respondents reported experiencing an injury in the past year, much less than reported in recent study of government laboratories (Schröder et al., 2016) in which over 50% of sample of government laboratory had experienced at least one injury. Taken together, the present sample may have been biased towards a greater sensitivity to safety issues and better safety performance.

4.3. Follow-on research

A better understanding of the factors that underlie many safety-related decisions and at-risk behaviors requires better behavioral assessment tools. Toward that end, the current project developed and administered two DCEs for quantifying the influence of several factors related to the topic of laboratory safety decision making. This study was innovative in several important ways. First, discrete-choice methods were extended to occupational safety concerns and more specifically to laboratory safety concerns. A second innovation was that the DCE technique was extended beyond the traditional analysis of tangible commodities or goods (and their features or attributes) to the analysis of more ambiguous influencing factors such as behavioral, social, or context-related factors and conditions. Although DCEs have been used extensively to assess consumer preferences, marketing trends, health behavior, and many other topics, to the best of our knowledge they have not been used in occupational safety research.

The theoretical and methodological foundations of DCEs appear to be suitable for addressing a wide range of occupational safety concerns where the objective is to better identify the factors that give rise to certain decisions or behaviors. Although the current project illustrated the promise of DCEs in evaluating factors that influence safety-related choices of laboratory workers in two different hypothetical scenarios, many other applications can be envisioned. For example, DCEs are well suited for assessment of worker preferences among various safe work practices and use of PPEs. Indeed, DCEs have been used extensively to assess consumer preferences and trade-offs with respect to tangible goods and products, and DCEs are similarly suitable for assessing worker preferences among different occupationally relevant PPEs, which also have tangible characteristics and quantifiable features. Furthermore, applications of DCE methods to assess worker preferences around PPE adoption would be aligned with existing calls for more research to identify the barriers against workers' decisions to use the following: (a) fall protection in construction, forestry industries, or wholesale/retail sectors (Kaskutas et al., 2009; Mroszczyk, 2008; Slappendel, Laird, Kawachi, Marshall, & Cryer, 1993); (b) seat belts in heavy machinery and commercial and fire-service vehicles (Bergoffen et al., 2005; Donoughe, Whitestone, & Gabler, 2012; Retzer, Hill, & Pratt, 2013); (c) hearing protection in manufacturing settings (Tak, Davis, & Calvert, 2009); and (d) safe patient handling techniques in health care settings (Koppelaar, Knibbe, Miedema, & Burdorf, 2009). A recent discrete choice experiment to identify factors that may promote hand hygiene practices in nurses (Zhao, Yang, Huang, & Chen, 2018) serves as a good example of factors affecting safety-related decisions in health care settings.

Beyond analyses of preferences for tangible, safety-related commodities or goods, DCEs may also help meet calls for greater research on safety climate, and, specifically, on investigating behavioral and situational factors associated with safety culture (e.g., Steward, Wilson, & Wang, 2016). Indeed, the attributes varied in the present DCE scenarios exemplify some of the same factors thought to underlie safety climate perceptions, such as management decision making, organizational safety norms and expectations, and safety practices, policies, and procedures that communicate organizational commitment to safety (Hahn & Murphy, 2008). However, in contrast to traditional safety climate perception surveys, which ask individuals to rate their agreement with several different statements about safety one at a time, DCEs allow individuals to make choices in the context of multiple behavioral, social, context, or organizational factors present simultaneously. Furthermore, by using realistic scenarios to frame specific safety-related dilemmas, DCEs are one of other promising approaches that use hypothetical scenarios to assess what workers might do when they encounter hazards and risks (e.g., Jorgensen, 2017). The information gained from DCEs may also identify educational topics for greater emphasis during safety workshops (cf. (Miller, 2019)) to more effectively influence laboratory workers' perceptions and values regarding laboratory safety.

5. Practical application

The DCE paradigm has a rich history and proven utility, and the extension of this method to occupational safety challenges shows a similar promise. A DCE offers safety researchers and professionals a systematic method for quantifying the relative influence of various factors on safety decisions and practices. The method can be carried out in an efficient manner using a survey format suitable for many different settings and worker populations. The use of DCEs in the present study of laboratory safety decisions and practices provided a better understanding of the factors that underlie laboratory workers' willingness to report safety incidences and comply with safety policies concerning PPE use. Specifically, incident reporting and use of PPE were influenced primarily by workers' perceptions of risk of exposure and severity of risks to health and safety. This finding suggests the importance of providing laboratory workers with adequate and effective education and training on the hazards and risks associated with their work.

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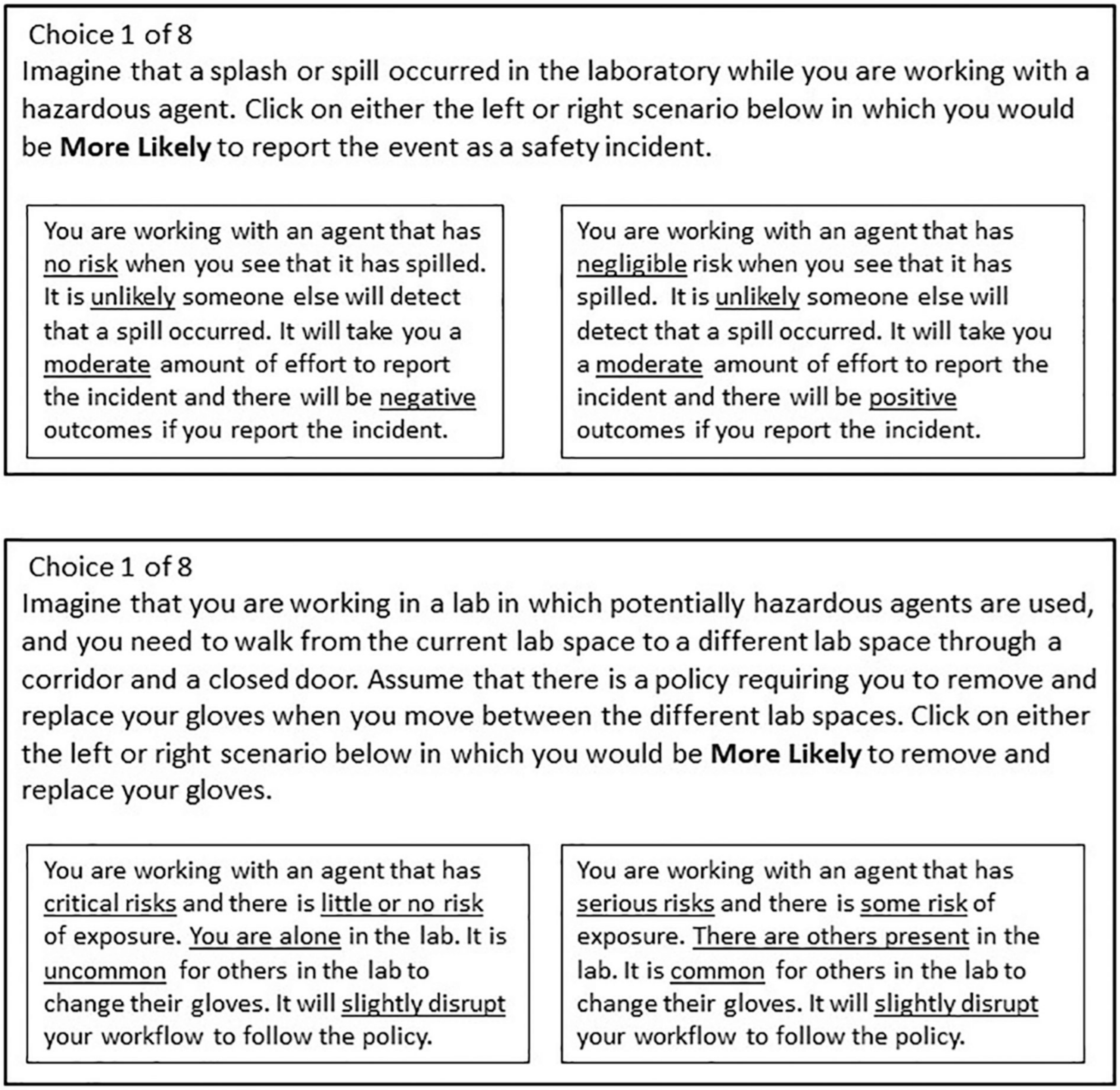

Fig. 1.

Examples of a choice question from the Reporting DCE (upper panel), which assessed the decision to report a spill of a hazardous agent, and PPE DCE (lower panel), which assessed the decision to wear protective gloves while working with a hazardous agent. A mouse click on either the left or the right alternative changed the box color to red and recorded the selection. The underlined levels of attributes in the descriptions of each alternative scenario varied systematically across the eight choice sets in each DCE.

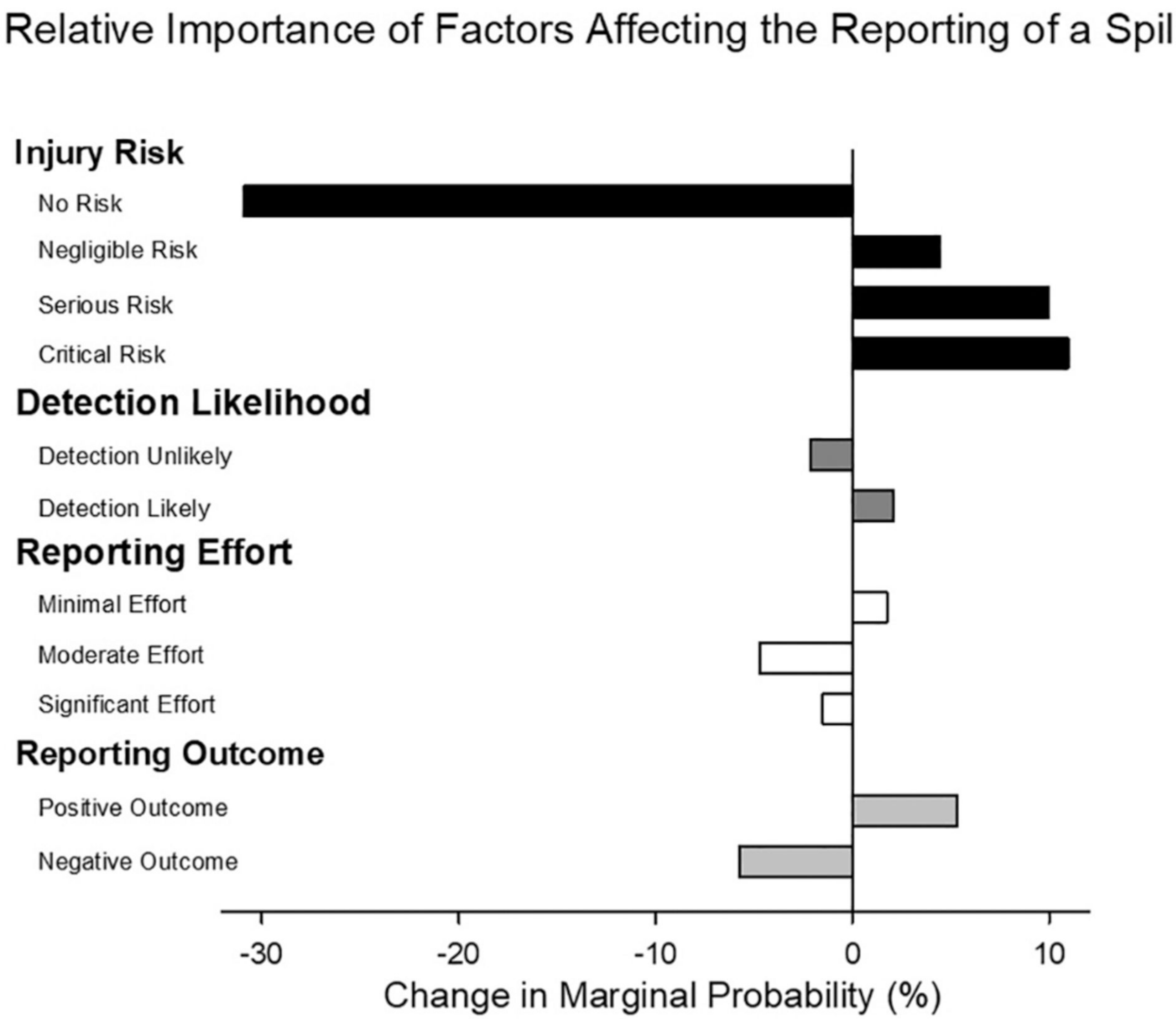

Fig. 2.

Results of the Reporting DCE showing the simulated change in marginal probabilities when choosing an alternative with the specific attribute level relative to the average choice probability on that alternative. In this scenario, comparing the change in probabilities across the different attribute levels indicates the relative importance of each attribute level on decisions report a safety incident. Positive percentages indicate attribute levels are associated with increased choice frequency; negative percentages indicate attribute levels are associated with decreased choice frequency.

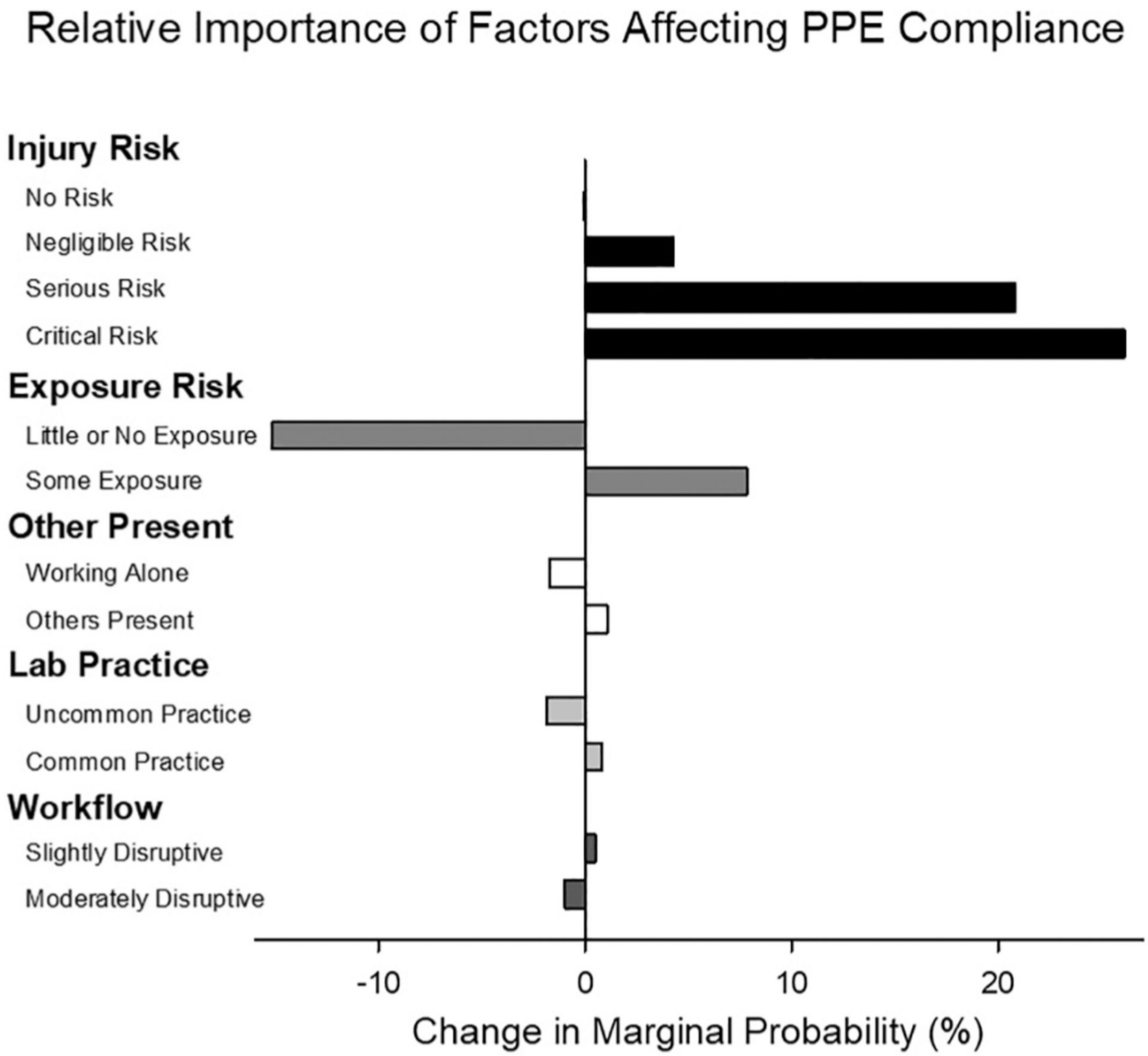

Fig. 3.

Results of the PPE DCE showing the simulated change in marginal probabilities when choosing an alternative with the specific attribute level relative to the average choice probability on that alternative. In this scenario, comparing the change in probabilities across the different attribute levels indicates the relative importance of each attribute level on decisions to wear protective gloves. Positive percentages indicate attribute levels are associated with increased choice frequency; negative percentages indicate attribute levels are associated with decreased choice frequency.

Table 1

List of attributes and levels of each attribute tested in the DCEs.

Attributes	Levels
Reporting DCE (Scenario: Reporting a spill of a hazardous agent)	
Risk Severity	None, Negligible, Moderate, Serious, Critical
Detection Likelihood	Unlikely, Likely
Reporting Effort	Minimal, Moderate, Significant
Reporting Outcome	Negative, Positive
PPE DCE (Scenario: Proper use of protective gloves)	
Risk Severity	None, Negligible, Moderate, Serious, Critical
Exposure Risk	Little or None, Some
Others Present	"You are alone," "There are others present"
Lab Practice	Uncommon, Common
Work Flow	Slightly Disruptive, Moderately Disruptive

Table 2

Sample characteristics, safety experience, and incident reporting behaviors.

Characteristic	% of Sample
Employment type	
FTE Employee	82.11%
FTE Fellow	17.89%
Years of experience	
0–5	3.25%
6–15	31.71%
16–25	28.46%
26 or more	36.59%
Biosafety levels	
No biohazards	22.38%
BSL-1	26.19%
BSL-2	37.14%
BSL-3	11.90%
BSL-4	1.43%
I do not know	0.95%
Service on a safety committee	
Yes	45.08%
No	54.92%
Injuries experienced[1]	
No	95.08%
Yes	4.92%
Safety incidents reported[1]	
0	81.97%
1	11.48%
2	4.10%
3	0.82%
4+	1.64%
Safety incidents experienced but not reported[1]	
0	95.08%
1	4.10%
2	0.82%
3	0.00%
4+	0.00%
Safety incidents witnessed but not reported[1]	
0	90.08%
1	4.96%
2	4.13%
3	0.83%

Characteristic	% of Sample
4+	0.00%
Safety near misses experienced[1]	
0	78.51%
1	8.26%
2	8.26%
3	3.31%
4+	1.65%
Deviations from safety procedures[1]	
0	83.61%
1	5.74%
2	7.38%
3	0.00%
4+	3.28%

[1] In the past year.

Table 3

Respondent scores on selected survey subscales.

Scale	Minimum Possible	Maximum Possible	Mean	Standard Deviation
CFSC	24	42	35.05	4.59
Delay Discounting (AUC)	0.00	0.98	0.66	0.22
Job Routineness	5	18	11.28	2.78
Safety Knowledge and Skills	11	20	16.45	2.34
Positive/Negative Feedback	6	19	13.89	2.92
Safety Climate: Management	25	80	57.37	11.78
Safety Climate: Supervisor	24	80	56.14	12.15

CFSC = Consideration of Future Safety Consequences; AUC = Area under the curve.

Table 4

Spearman correlations of selected factors and variables.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Years Experience	—														
2. Biosafety Level	0.04	—													
3. Job Routineness	0.05	0.11	—												
4. Knowledge and Skills	0.07	0.08	−0.24	—											
5. Feedback	−0.18	0.04	−0.15	**0.28** *	—										
6. CFSC	0.16	−0.13	−0.14	**0.42** *	0.16	—									
7. AUC	0.17	−0.09	−0.06	0.12	−0.19	−0.00	—								
8. SC-Management	0.09	−0.05	−0.16	**0.39** *	0.14	**0.32** *	0.17	—							
9. SC-Supervisor	−0.04	−0.12	−0.09	**0.33** *	**0.29** *	0.13	0.04	**0.50** *	—						
10. Safety Committee	0.15	0.12	−0.15	0.21	−0.09	0.07	0.26	0.02	0.09	—					
11. Incidents Reported	0.04	0.10	0.05	0.07	−0.06	0.06	0.05	**−0.22** *	0.00	**0.22** *	—				
12. Incidents Not Reported	−0.06	−0.08	0.04	−0.20	0.02	0.03	−0.04	0.01	−0.03	−0.13	**0.19** *	—			
13. Incidents Witnessed	−0.05	**0.19** *	0.14	−0.02	−0.01	0.07	−0.09	−0.17	−0.15	−0.03	0.12	**0.18** *	—		
14. Injury Experienced	0.18	0.04	0.13	0.04	−0.08	0.05	0.07	−0.06	−0.05	0.02	0.08	−0.05	**0.31** *	—	
15. Near Miss Experienced	−0.12	**0.20** *	−0.08	−0.05	0.07	−0.12	0.17	−0.08	−0.06	0.12	**0.35** *	**0.31** *	0.16	−0.12	—

Note. CFSC = Consideration of Future Safety Consequences. AUC = Area under the curve. SC = Safety Climate.

* = $p < 0.05$.

Table 5

Multinomial logit results for the Reporting DCE, which assessed the decision to report a spill of a potentially hazardous agent. Attribute levels noted with asterisks significantly influenced participants decisions to report the incident.

Attributes and Levels	Coefficient	Standard Error	*z*	*p* value	Confidence Interval
Constant	−0.3446	0.4511	30.76	0.4449	−1.23 to 0.54
Injury Risk					
No Risk (Ref)	—	—	—	—	—
Negligible Risk	0.4625	0.2644	1.75	0.0803	−0.06 to 0.98
Serious Risk	1.8094***	0.2822	6.41	0.0000	1.26–2.36
Critical Risk	2.7856***	0.3698	7.53	0.0000	2.06–3.51
Detection Likelihood					
Detection Unlikely (Ref)	—	—	—	—	—
Detection Likely	0.3197*	0.1523	2.10	0.0358	0.02–0.62
Reporting Effort					
Minimal Effort (Ref)	—	—	—	—	—
Moderate Effort	−0.4685**	0.1799	−2.60	0.0092	−0.82 to −0.16
Significant Effort	−0.1684	0.1603	−1.05	0.2936	−0.48 to 0.15
Perceived Outcome (of reporting)					
Positive Outcome (Ref)	—	—	—	—	—
Negative Outcome	−0.8518***	0.1443	−5.90	0.0000	−1.13 to −0.57
Covariates					
Years Experience	0.3408**	0.1158	2.94	0.0032	0.11–0.57
Safety Committee Experience	−0.8141***	0.2155	−3.78	0.0002	−1.24 to −0.39

Note. Number of observations = 746 (123 respondents × 8 choices minus 238 missing values).

R-squared = 0.198; log-likelihood = −314.75; Akaike information criterion = 649.5; Ref = Reference level.

* $p < 0.05$.

** $p < 0.01$.

*** $p < 0.001$.

Table 6

Multinomial logit results for the PPE DCE, which assessed the decision to remove and replace protective gloves according to a hypothetical PPE policy as described in the scenario. Attribute levels noted with asterisks significantly influenced participants decisions to wear PPE.

Attributes and Levels	Coefficient	Standard Error	*z*	*p* value	Confidence Interval
Constant	0.1348	0.1361	0.99	0.3221	−0.13 to 0.40
Risk of Injury					
No Risk (Ref)	—	—	—	—	—
Negligible Risk	0.4126	0.2233	1.85	0.0646	−0.03 to 0.85
Serious Risk	2.2245*	0.2569	8.66	0.0000	1.72–2.73
Critical Risk	2.9117*	0.2262	12.87	0.0000	2.47–3.36
Exposure Risk					
No Exposure (Ref)	—	—	—	—	—
Some Exposure	1.4557*	0.1632	8.92	0.0000	1.14–1.78
Presence of Others					
Working Alone (Ref)	—	—	—	—	—
Others Present	0.2032	0.1189	1.71	0.0874	−0.03 to 0.44
Laboratory Practice					
Uncommon Practice (Ref)	—	—	—	—	—
Common Practice	0.1985	0.1112	1.78	0.0743	−0.02 to 0.42
Workflow					
Slightly Disruptive (Ref)	—	—	—	—	—
Moderately Disruptive	−0.1083	0.1382	−0.78	0.4330	−0.38 to 0.16

Note. Number of observations = 735 (123 respondents × 8 choices minus 249 missing values).

R-squared = 0.373; log-likelihood = −315.24; Akaike information criterion = 646.5. Ref = Reference level.

* $p < 0.0001$.