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Summary

Background

Intelligence reduces the risk of accidents. Prior tests of this reasonable hypothesis have produced associations that are too weak to be of much theoretical or practical importance. However, intelligence is most valuable when complex patterns of information must be processed. In an occupational setting, intelligence may have a strong effect on accident rates only when work involves a complex set of hazards.

Objective

The study hypothesis was that the association of intelligence with accidents would be strongest in occupations with complex workplace hazards.

Approach

Accidental injury was investigated over the first-term enlistment of a cohort of 183,575 U.S. Navy recruits who entered the service between January 1, 1990, and December 31, 1998. The accident criterion was hospitalization for an injury with a Standard NATO Agreement code indicating that the injury was an accident. Intelligence was measured by Armed Forces Qualification Test scores with conversion from percentile rankings to equivalent normal scores. Occupational hazards were measured by job characteristic ratings provide by senior enlisted personnel familiar with the requirements of 54 entry-level occupations. The average AFQT for the occupation and the proportion of women were also included as occupational characteristics. Hierarchical generalized linear models were developed to represent the joint effects of individual-level variables (i.e., gender, intelligence) and occupational characteristics (e.g., physical demands).

Results

The association of intelligence with accidents varied across occupations in the initial analyses. Follow-on analyses led to the development of a quadratic equation to describe the association of intelligence with accidents. The coefficients for intelligence in this revised equation were invariant across occupations. The intercept for the revised model varied across occupations, so the overall level of risk differed between occupations. At the occupational level, the average intelligence of occupational incumbents and the physical hazard level of an occupation predicted injury rates.

Discussion

Intelligence appears to have little effect in determining who will be an accident victim in the U.S. Navy enlisted population. Intelligence is associated with lower risk only for personnel with well above-average intelligence and those individuals are rarely assigned to hazardous occupations. Intelligence matters more when considered in the aggregate. The average intelligence of coworkers may determine the frequency of exposure to risk or temptation to follow bad examples. For example, forgetting to follow safety rules can increase risk to others and sets an example that others may choose to follow. Thus, having coworkers with lower average intelligence can expose a sailor to more secondhand risk and opportunities for behavioral contagion. The effects of coworkers' behavior may be particularly important because they extend beyond the job setting if people socialize with colleagues.

Reduced risk of injury should be one expression of intelligence. Past research supports this apparently logical statement, but only weakly. Meta-analysis indicates a weak (r = -.11) association of intelligence with accidents (Arthur, Barrett, & Alexander, 1991). Additional studies would not change the picture (Ferguson, McNally, & Booth, 1981; Hansen, 1989; Jin, Araki, Wu, Zhang, & Yokoyama, 1991; O'Toole, 1990; Poole, Lewis, Devidas, Hauser, Martin, & Thomae, 1997). Evidently, the association of intelligence with accidents barely meets Cohen's (1988) minimum standard for identifying associations with practical or theoretical importance.

Perhaps intelligence only helps avoid accidents under some conditions. Logic suggests that intelligence cannot help a person avoid nonexistent risks. Also, intelligence may be of little value when a single risk factor dominates a situation. Intelligence may be important primarily when a person faces multiple hazards that form complex risk patterns. In this case, rapid processing of the information, which is one element of intelligence, may be required to avoid accidents. Smith and Kirkham (1982) applied this rationale to explain why more-intelligent individuals had fewer automobile accidents at intersections but not in other driving settings.

The complexity argument can be applied to U.S. Navy enlisted occupations. Those occupations have complex job characteristic profiles (Carter & Biersner, 1982; Reynolds, Barnes, Harris, & Harris, 1992). Some of the profile elements are associated with higher risk of injury. These elements include requirements for physical exertion, perceptual speed, hazardous environmental conditions (e.g., heat, crowding, noise), manual labor, and working with machinery (Vickers, Vickers, & Hervig, 2006). Some occupations combine multiple hazards; other occupations are virtually hazard free (Carter & Biersner, 1982; Reynolds et al., 1992). Therefore, the complexity of the hazards that must be monitored varies across enlisted occupations. This study tested the hypothesis that intelligence would be more strongly related to accidents in those enlisted occupations with greater requirements for processing hazard information.

Methods

Subjects

Study participants were U.S. Navy enlisted personnel who began basic training between January 1, 1990, and December 31, 1998. The cohort was restricted to individuals who had enlisted for a 4-year term of duty and entered the service at a pay grade of E-3 or less. This cohort was further restricted to individuals who met the occupational criteria described in the following section of these methods. These restrictions produced a basic sample size of 183,575 sailors.

Occupation

Information in the Career History Archival Medical and Personnel System (CHAMPS; Gunderson, Garland, Miller, & Gorham, 2005) database was used to determine occupation. This database includes records of administrative events occurring during each sailor's naval service. Entries record promotions, demotions, change of duty station, hospitalization, and so forth. The sailor's Navy Enlisted Classification (NEC) code at the time of the event is listed on each record. Recruits typically enter the service as a Fireman recruit, Airman recruit or Seaman recruit. This initial general assignment is followed by later entry into a specific enlisted occupation. Occupational classification was based on these later assignments as determined from CHAMPS records. The typical individual's records showed only a single NEC after assignment to an occupation. In these cases, that NEC defined the sailor's occupation. A small percentage of cases with more than 1 NEC were dropped from the analysis.

Two criteria determined which occupations were included in the analyses. Occupational hazard ratings had to be available. This requirement limited the analyses to entry-level occupations (see Occupational Hazards below). The cumulative person-years of observation for the occupation had to be large enough to have stable estimates of accident rates. Vickers, Hervig, and White (1997) found that including occupations with very small populations and, therefore, relatively few person-years of observation, introduced noise into the analysis that tended to obscure relationships. The present analyses were limited to occupations represented by a minimum of 600 person-years of observation. Application of these criteria limited the analyses to 54 occupations with 183,575 incumbents observed for a cumulative period of 650,683 person-years.

Accident Rates

Accident rates were based on CHAMPS hospitalization records. Accidental injuries were identified by the Standard NATO Agreement (STANAG) code for the admission. This code indicates the cause of the injury that was the reason for admission, including whether injury was intentional or unintentional (Amoroso, Bell, Smith, Senier, & Pickett, 2000). Only unintentional injuries were included in this study. The injury rate computation for each occupation was

Rate = Number of Accidents * (100,000/Number of Person-Years of Observation)

The number of accidents was a count of the hospitalizations with STANAG codes indicating accidental injury. Separate counts were made for those personnel assigned to each occupation. Injuries that occurred in basic training were excluded from the count. The code for unit assignment at the time of injury provided the means of identifying those accidents.

The accident count was limited to injuries occurring during the first 4 years of the first enlistment. This restriction ensured that accidents did not happen during a second enlistment. The restriction also ensured that the sailors were still serving in entry-level occupations, thereby matching the accident rates to the occupational hazard assessments. Every individual who completed his or her first-term enlistment contributed 4 years to the years of observation even though some served longer because they extended their tour of duty. The number of days served between entry into basic training and the date of discharge was computed and converted to years of exposure for individuals who did not complete their enlistment.

Occupational Hazards

Ratings of occupational conditions demand were taken from the Reynolds et al. (1992) Job Activities Inventory, an instrument that included ratings of occupational requirements for 107 different job-related characteristics. This instrument was completed by senior enlisted personnel (96% E-6 or E-7) in the occupation. Each characteristic was rated for its importance to job performance. The ratings were made using a 5-point scale with “Not Very Important,” “Somewhat Important,” “Important,” “Very Important,” and “Extremely Important” as response anchors. These responses were scored 1, 2, 3, 4, and 5, respectively. Respondents also had the option of responding “Not Applicable.” Reynolds et al. (1992) treated this response option as missing data. However, the present analyses interpreted this response as evidence that the characteristic in question simply was not a factor in the occupation. A “Not applicable” response therefore was assigned a score of 0 in the computations. One reason for this decision was that the Reynolds et al. (1992) procedure produced average scores that were based on just a subset of raters when “Not Applicable” was chosen by some rater(s) in an occupation. This response option formed a sizable proportion of the responses for some characteristics in some occupations. The average score for the subset of respondents who assigned some importance to the characteristic would be misleading in such cases.

Previous analyses of the relationships between these ratings and accident rates indicate that the ratings can be reduced to a single index of hazards (Vickers et al., 2006). The index includes the scores for 38 of the 107 items. The complexity of this overall hazard index is indicated by the fact that it covers 5 job factors identified by Reynolds et al. (1992): *Physical Ability Demands*, *Perceptual Speed Demands*, *Working with Machinery*, *Poor Working Conditions*, and *Manual Labor*. The index also included 12 specific job characteristics (e.g., awareness of body position and balance). The general hazard index thus is a reasonable summary of the complexity of job hazards.

Intelligence

The Armed Forces Qualification Test (AFQT) was the measure of general intelligence. Scores on this test are strongly related to standard measures of general intelligence (i.e., psychometric *g*, cf., Ackerman, 1988). Personnel records report AFQT scores as percentile standings. Percentile standing is not a proper scale for analysis because the difference in intelligence represented by a single percentile is variable. For example, the 1% difference between the 50th and 51st percentiles equals .025 standard deviations in raw score units. The 1% difference between the 90th and 91st percentiles equals .06 raw score standard deviations. The 1% difference between the 98th and 99th percentiles corresponds to .27 standard deviations. To correct for this scaling effect, the percentiles were converted to *z*-scores, with the assumption that intelligence is normally distributed in the general population. Recruitment standards produce a truncated distribution within the military services by excluding individuals with low scores.

Analysis Procedures

The HLM 6 computer program (Raudenbush, Bryk, Cheong, & Congdon, 2004) was employed to conduct the primary statistical tests of hypotheses. The hierarchical generalized linear model (HGLM) procedures in this analysis package provide appropriate statistical inferences for logistic regression when individual cases are nested within a higher-level category (Raudenbush & Bryk, 2002). In the present instance these methods are required because individual sailors are nested within occupations. The analyses used the logit link function to transform the model to a linear form for analysis. HGLM produces models that describe relationships at 2 levels. A fixed-effect, level-1 model was defined the basic relationship between accidents and gender and intelligence. The general form of the level-1 model was

$$\mathrm{Log}[p/(1-p)] = b_0 + (b_1 * \mathrm{AFQT}) + (b_2 * \mathrm{Gender}) + e$$

The level-2 model consisted of a set of equations describing variation in the level-1 coefficients. The simplest general expression of the level-2 elements would be

$$b_i = \gamma_0 + \gamma_j W_j + u$$

The dependent variable, a coefficient from the level-1 equation, is expressed as a function of characteristics of the level-2 units, indicated by Wj, plus random variance, u. If the analysis indicates that there is no random variance in a level-1 component, the equation for that component is simply γ_0, the fixed-effect, level-1 estimate for the parameter. If the random variance is significantly greater than zero, the level-2 equation includes at least γ_0 and u. Terms for $\gamma_j W_j$ are added when some attributes of the level-2 units predict the estimated deviation from the fixed-effects model. When this is the case, combining level-1 and level-2 equations into a single function results in an expression in which the logit coefficient of a level-1 predictor varies as a function of the level-2 characteristic. The elements of the equation are directly analogous to the cross-product terms in moderated regression. In the present analyses, parameter estimates were derived using the restricted maximum likelihood method. Determinations of which effects were significant were based on a unit-specific model with robust error estimates. Significance tests were 1-tailed given a priori expectations that intelligence would decrease the risk of accidents and job hazards would increase the risk of accidents.

Secondary analyses were carried out with SPSS-PC (1998a, 1998b). These analyses included exploratory assessments of associations between occupational characteristics and the logistic regression coefficients. Those associations tested the contingency hypotheses by determining whether the estimated effect of intelligence was related to the hazard level of an occupation.

Results

Initial Model

Level- 1 Element. Level-1 elements of the analysis consisted of the equations that employed individual AFQT scores and gender as predictors of individual accidents. The analyses emphasized the assessment of the random variance component for the regression coefficients.

- Initially, the random variance component was significant for the intercept, χ^2 = 200.07, 52 *df*, p < .001, and AFQT, χ^2 = 86.38, 52 *df*, p = .002, but not for gender, χ^2 = 66.88, 52 *df*, p = .080. The variance components for intercept, χ^2 = 212.64, 53 *df*, p < .001, and AFQT, χ^2 = 87.38, 53 *df*, p = .002, remained significant with gender as a fixed effect.
- When converted to reliability coefficients (cf., Raudenbush & Bryk, 2002), the random variance component was a large effect for the intercept, r_{xx} = 0.593, and a moderate effect for AFQT, r_{xx} = 0.263.

Level-2 Element. The level-2 model used occupational characteristics to account for the variation in the intercept and hazard coefficients across occupations. Occupational hazards were weak predictors of the Bayes estimate of the AFQT regression coefficients (Table 1). The associations were in the predicted direction, but too small to be statistically significant. This result contrasted with the moderate negative association with average AFQT.

Curvilinear Model

The relationship of average AFQT to the variation in occupational coefficients suggested the existence of a curvilinear level-1 relationship. An exploratory plot of the values indicated that the relationship was linear. In calculus, a linear relationship between level and slope is the derivative of the quadratic function (Strang, 1991). This functional form was tested in an exploratory level-1 logistic regression that produced

$$\log[p/(1-p)] = .112*A - .150*A^2 + .073*G - 3.695 \quad \text{(Equation 1)}$$

Two-tailed Wald tests indicated that the linear, χ^2 = 5.28, 1 *df*, p = .022, and quadratic, χ^2 = 20.42, 1 *df*, p < .001, coefficients were significant. The gender coefficient was not significant, χ^2 = 2.74, 1 *df*, p = .098.

Table 1. Occupational Characteristics as Predictors of Coefficient Variance

	Intercept	AFQT Slope
General Hazards	.327	.213
Physical Demands	.358*	.269
Perceptual Skill	.098	.013
Work with Machinery	.303	.140
Poor Work Conditions	.308	.213
Manual Labor	.299	.157
Miscellaneous	.299	.290
Average AFQT	-.369*	-.480*
Gender	.109	.071

**p* < .006, 1-tailed, *N* = 54 occupations. The criterion is a Bonferroni adjustment based on 9 significance tests and an experiment-wide error of *p* < .05.

Level-1 Element. Adding the curvilinear component to the level-1 model eliminated the random variance component in the AFQT coefficient. With this modification, the random variance component was not significant for the gender, $\chi^2 = 66.78$, 52 *df*, $p = .081$, linear AFQT linear, $\chi^2 = 62.86$, 52 *df*, $p = .144$, or quadratic AFQT, $\chi^2 = 44.30$, 52 *df*, $p > .500$, terms. The random variance component for the intercept was significant, $\chi^2 = 185.17$, 52 *df*, $p < .001$.

The second iteration of level-1 curvilinear model eliminated the random variance component for all coefficients except the intercept. The resulting level-1 model was

$$\log[p/(1-p)] = .126*G + .151*A - .130*A^2 – 3.66 \quad \text{(Equation 2)}$$

All Equation 3 coefficients were statistically significant (gender, $t = 2.99$; A, $t = 2.79$; A^2, $t = -3.96$, 183,571 *df* for each, $p < .001$ for each; intercept, $t = -109.58$, 53 df, $p < .001$). The random variance in the intercept was statistically significant, $\chi^2 = 249.90$, 53 *df*, $p < .001$, $r_{xx} = .648$.

Level-2 Component. Preliminary analyses showed that the pattern of associations between the random variance in the intercept and the predictors was similar to the pattern for the intercept in the original linear AFQT model. Those findings focused attention on AFQT. General Hazards was the primary index of occupational hazards based on earlier evidence that separate effects of individual hazards could not be clearly identified at the occupational level. Results were:

- Average AFQT predicted occupational variation in the intercept, $t = -3.70$, 52 *df*, $p = .001$.
- General Hazards predicted occupational variation in the intercept, $t = 2.69$, 52 *df*, $p = .005$.
- When combined, AFQT, $t = -3.23$, 51 *df*, $p = .003$, and General Hazards, $t = 1.76$, 51 *df*, $p = .042$, contributed independently to the prediction of occupational differences in the intercept.

The final model was

Level-1

$$\log[p_i/(1-p_i)] = -3.673 + .119*G_i + .183*A_i - .138*A_i^2$$

Level-2

$b_0 = -3.673 - .269*A_j + .060*H_j + u_0$
$b_1 = .119$
$b_2 = .183$
$b_3 = -.138$

Combined

$$\log[p_i/(1-p_i)] = -3.673 - .269*A_j + .060*H_j + .119*G_i + .183*A_i - .138*A_i^2$$

where A_j is the average AFQT score for the occupation and H_o is the General Hazards level for the occupation.

The residual variance component for each model can be examined to evaluate the explanatory power of the predictors in the level-2 equation. The variance component for b_0 in the model with no level-2 predictors was u_0 =.03665. Adding A_o to the initial model as a predictor of b_0 reduced the variance component by 19.3% (u_0 =.02957). Adding H_o to the initial model reduced the variance component by 8.8% (u_0 = .03342). Combining A_o and H_o as predictors reduced the variance component by 20.7% (u_0 = .02908). However, even with this reduction the residual variance component was significant, $\chi^2 = 222.15$, 51 *df*, $p < .001$.

Illustrating Effects

Effect sizes in logistic regression can be expressed several ways (Long, 1997). In the present case, the effects were evaluated by comparing reference cases. Typical probability of injury was defined as the probability for a male of average intelligence. The reference case was a male sailor of average intelligence who worked in an occupation in which the average AFQT score was 0.56, the midpoint of the range of occupational averages (i.e., Aj = 0.56), and the General Hazards rating was 2.50, the midpoint of the rating scale.

Effects were illustrated by computing probability estimates for other prototypical cases and comparing those estimates to the value for the reference case. The other prototypical cases were designed to illustrate the importance of a single factor in the equation. This end was accomplished by changing the value of a single variable. For example, the probability for a reference female participant was computed with the same average intelligence, occupational hazard, and individual intelligence values as for males. The only difference was that the code for male (1) was replaced with the code for female (0). The relationship between this case and the typical probability of injury was expressed as a relative risk ratio (RR). These assessments produced:

- Reference Case: The probability of injury was $p = .0278$.
- Gender: The probability of injury for the prototypical female sailor was $p = .0248$ (RR = 2.48/2.78 = 0.89).
- Intelligence. The probability of injury at the lower boundary of the range of AFQT scores, $z = -0.53$, was $p = .0244$ (RR = 0.88). The probability at the upper boundary, $z = 2.33$, was $p = .0203$ (RR = 0.73). The AFQT score with the highest probability of injury was $z = 0.66$, $p = .0295$, RR = 1.06.
- Occupational Hazards: For a low score, 0.50, the probability was $p = .0247$, (RR = .89). For a high score, 2.50, the probability was .0312 (RR = 1.12).

- Occupational AFQT: The probability at the low extreme, -.07, was $p = .0328$ (RR = 1.18). The probability at the high extreme was $p = .0236$ (RR = .85).
- The ratio of the highest to the lowest probability for each factor provided an overall index of sensitivity to that characteristic. This ratio was highest for individual intelligence (RR = 1.45), followed by average intelligence in the occupation (RR = 1.39), followed by General Hazards (RR = 1.26), and gender (RR = 1.12).

Discussion

The initial analyses supported the hypothesis that intelligence is more strongly related to accidents in hazardous occupations than in safer occupations. The association of intelligence with accidents varied across occupations. The differences were related to occupational hazard levels.

An incidental finding changed the picture. Average AFQT within an occupation was the best predictor of the AFQT regression coefficient for that occupation. This finding led to the addition of a quadratic AFQT term in the level-1 model. The AFQT regression coefficients in the revised model did not differ significantly across occupations. The initial study hypothesis was incorrect.

The revised model was an improvement. Parsimony is a desirable characteristic in theoretical models. The number of parameters in a model is one definition of parsimony (Popper, 1959). The revision replaced 54 occupation-specific linear coefficients with 1 quadratic coefficient, a clear gain in parsimony.

The revised model also simplified interpretation. The initial model was the HGLM equivalent of finding nonparallel regression lines in an analysis of covariance. The revised model was the equivalent of finding parallel regression lines. Nonparallel regression lines require complex interpretations based on regions of significant differences (Walker & Lev, 1953; Rogosa, 1980). Parallel regression lines mean that interpretations based on the differences in adjusted group means apply equally to all cases. In this case, the invariant level-1 coefficients meant that injury rates adjusted for the gender and intelligence applied to all personnel within an occupation.

The curvilinearity in the level-1 association of AFQT with injury was surprising. A consistent downward trend might have been considered more reasonable prior to the analysis. Two points supported the view that the curvilinear model was appropriate for the present data. First, the curvilinear trend was added on the basis of a clearly defined, moderately strong linear relationship between average AFQT and the linear regression slopes in the initial analysis. Second, the curvilinear component of the revised model had greater explanatory power than the linear trend (i.e., a larger Wald test). On the whole, however, it seems reasonable to require replication before the curvilinearity finding becomes the basis for complex explanatory models.

The level-2 results reinforced a previous finding. Vickers and Hervig (2005) found that occupational personality profiles predicted accident rates after controlling for occupational hazards. This result pointed to the importance of coworkers' behavior as an injury risk factor. The present results again demonstrate that both physical hazards and coworker characteristics must be considered to fully characterize occupational risks. Secondhand risk and behavioral contagion were suggested as mechanisms for the coworker effects. Secondhand risk occurs when one person's behavior increases the risk of injury for people around the individual. Behavioral contagion occurs when a person who observes others' failure to engage in appropriate behavior adopts similar behavior. These generic mechanisms could apply to the present intelligence findings. If low intelligence is expressed on the job as poor decision making or forgetting safety regulations, the associated behavior can cause risk to colleagues and set an example to follow.

The revised model had moderate explanatory power. At the individual level, the risk ratios comparing high and low extremes fell between 1.1 and 1.5. These values would be considered small effects in most research. Thus, the evidence still indicates that the association of intelligence with accident rates is weak, even controlling for exposure to occupational hazards. At the occupational level, hazards and intelligence explained 20% of the variance in accident rates. This explanatory power represents a moderate effect size (Cohen, 1988).

Every study has limitations. The injury criterion was limited to accidents that cause severe injury. These events may not be representative of accidents in general. The criterion combined on-duty and off-duty accidents. Physical hazards predict on-duty accidents better than off-duty accidents (Vickers & Hervig, 1999), so separating the two types of accident might increase the accuracy of the model.

The focus on intelligence may be a limitation. The hypothesized effects of intelligence may really derive from its association with working memory, a cognitive capacity that affects the speed and accuracy of processing complex information. Working memory is positively related to intelligence, but the strength of association is uncertain. Ackerman, Beier, and Boyle (2005) suggested a moderate association, $r = .479$. Kane, Hambrick, and Conway (2005) and Oberauer, Schulze, Wilhelm, and Süß (2005) argued for a stronger relationship, but still fixed the upper limit of the association at $r = .850$. If intelligence is really only a weak proxy for working memory, susceptibility to accidents would be more clearly defined with measures of working memory.

The study had strong points as well as limitations. Coverage of a wide range of occupations with detailed profiles of occupational hazards was a strong point. The face validity of the criterion was important. Past research demonstrating convergent and discriminant validity strengthens the interpretation of both the injury criterion and the hazard measures (Vickers & Hervig, 1998). Multilevel modeling was essential to redefining the model. In particular, it is very unlikely that the curvilinear trend in the intelligence-accident function would have been identified without the use of these methods. Furthermore, combining explanatory variables from different levels provided a more complete explanatory model, thereby reducing the risk of omitted variable bias (James, Mulaik, & Brett, 1982).

In conclusion, the original hypothesis was wrong, but exploring it was productive. The exploration redefined the functional relationship of intelligence with accidents. If the resulting curvilinear model replicates, it could stimulate the development of a more complex conceptual approach to accidents and injury. The exploration also demonstrated that adjusted injury rates accurately represent occupational differences. This aspect of the findings provides a framework for any future studies conducted at the level of occupational differences. Finally, the exploration reinforced the importance of considering human dynamics along with environmental hazards when developing accident prediction models. These exploratory gains combined with the study limitations suggest constructive lines for future research.

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Intelligence reduces the risk of accidents. Empirical tests of this hypothesis have produced weak associations. This study tested a conditional form of the hypothesis: Intelligence reduces the risk of accidents in hazardous occupations. Multilevel modeling of hospitalization for accidental injury in 54 U.S. Navy enlisted occupations provided the empirical test of the conditional hypothesis. The final model included gender and intelligence as predictors at the individual level of analysis. Injury risk was a quadratic function of intelligence. Physical hazards and the average intelligence of occupational incumbents predicted occupational accident rates controlling for the gender and intelligence composition of the occupation. The conditional hypothesis was not supported, but the findings raised issues for further study. The curvilinear association of intelligence and injury rates will require explanation if it replicates. The independent association of coworker intelligence with occupational accident rates controlling for physical hazards reinforced the view that group processes are an important element of occupational accident models.

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