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Ensuring data quality and maximizing efficiency in coding agricultural and forestry injuries: Lessons to improve occupational injury surveillance

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ABSTRACT

Introduction: Specialized occupational injury surveillance systems are filling the gap in the undercount of work-related injuries in industries such as agriculture and forestry. To ensure data quality and maximize efficiency in the operation of a regional occupational injury surveillance system, the need for continued dual coding of occupational injury records was assessed. *Methods:* Kappa scores and percent agreement were used to compare interrater reliability for assigned variables in 1,259 agricultural and forestry injuries identified in pre-hospital care reports. The variables used for the comparison included type of event, source of injury, nature of injury, part of body, injury location, intentionality, and farm and agriculture injury classification (FAIC). *Results:* Kappa (κ) ranged from 0.2605 for secondary source to 0.8494 for event and exposure. Individual coder accuracy ranged from medium to high levels of agreement. Agreement beyond the first digit of OIICS coding was measured in percent agreement, and type of event or exposure, body part, and primary source of injury continued to meet levels of accord reaching 70% or greater agreement between all coders and the final choice, even to the most detailed 4th digit of OIICS. *Conclusions:* This research supports evidence-based decision making in customizing an occupational injury surveillance system, ultimately making it less costly while maintaining data quality. We foresee these methods being applicable to any surveillance system where visual inspection and human decisions are levied. *Practical Applications:* Assessing the rigor of occupational injury record coding provides critical information to tailor surveillance protocols, especially those targeted to make the system less costly. System administrators should consider evaluating the quality of coding, especially when dealing with free-text narratives before deciding on single coder protocols. Further, quality checks should remain a part of the system going forward.

1. Introduction

The agricultural, forestry, and fishing industries (AgFF) have consistently held the highest fatality rates of any other sector in the nation. The average worker fatality rate in these fields is seven times that of the national average, at 25.3 FTE versus 3.4 FTE (per 100,000 Full Time Employees) (Bureau of Labor Statistics, 2020). Further, public health surveillance systems commonly fail to attain numbers sufficiently representative of the impact of occupational morbidity among these industries, underrepresenting injury and acute events.

The Survey of Occupational Injuries and Illnesses (SOII) is a common source of data for nonfatal injuries and illnesses in the United States. While these data provide a snapshot into occupational morbidity, it does so through the collection of data for a random sampling of U.S. businesses while excluding the military, self-employed individuals, farms with less than 11 employees, and federal agencies (Bureau of Labor Statistics, 2015). Consequently, estimates are not truly representative of nonfatal injury and illness rates in smaller AgFF operations. As small-scale operations of this sort make up the majority of businesses in the Northeastern United States, large swathes of the AgFF industries ultimately go unaccounted for (Leigh, Marcin, & Miller, 2004; National Occupational Research Agenda, 2008; Ruser, 2008). Worsening this lack of representation, some ancillary reporting systems such as the Occupational Injury Surveillance of Production Agriculture (OISPA) have

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been discontinued due to unsustainable costs (Centers for Disease Control and Prevention, 2015).

There are numerous ongoing efforts to help fill this gap with accurate reporting. The National Children's Center for Agricultural Health and Safety monitor agricultural injuries through media reports, posted on the AgInjuryNews.org website. Data are gathered from news media, social media, and obituaries for intentional, unintentional, occupational, and non-occupational agricultural cases (Weichelt, Salzwedel, Heiberger, & Lee, 2018). The University of Nebraska Medical Center and Central States Center for Agricultural Safety and Health (CS-CASH) have been surveying self-employed farmers and ranchers since 2011. Their efforts allow for a more accurate understanding of injury rates, consequences, risk factors, and trends in their serviced region (Jadhav, Achutan, Haynatzki, Rajaram, & Rautiainen, 2017). The NIOSH Western States Division monitors the United States Coast Guard (USCG) investigative reports to develop a Commercial Fishing Incident Database (CFID) in order to identify hazards leading to death and/or injury within the fishing community. Their database is applicable at the national level, applying to all fishing industry workers (Case, Lincoln, & Lucas, 2018). Larson et al. developed a surveillance system to focus on migrants and seasonal workers. These workers are notoriously difficult to track accurately due to population movement, differences in definitions, duplicate counts, and a plethora of other hazards. To combat this, the Migrant and Seasonal Farmworker Enumeration Profiles Study (EPS) was created to gather accurate numbers at the county level, as well as state-level estimates for children and youths (Risto, 2021).

While not an exhaustive list of such systems, these efforts illustrate how more precise injury and illness rates are calculated, at a variety of costs. However, there remains a need to provide greater geographic coverage for these specific events and for systems to be comparable. This process is typically accomplished by human coders breaking apart the free-text data to assign consistent coding, often from the Occupational Injury and Illness classification (OIICS) and Farm and Agricultural Injury Classification (FAIC) systems, for example.

Established in 1992 by the Bureau of Labor Statistics, OIICS classifies occupational injuries, illnesses, and fatalities with four main categories: (1) nature of injury, (2) type of event or exposure, (3) source of injury or illness, and (4) body part affected (Bureau of Labor Statistics, 2012). Each category has up to four levels of increasing detail. The OIICS codes are available in a tree format online and are downloadable in desktop version of the tree structure and as Excel files for OIICS version 2.01, which has more than 3,000 individual codes.

Departing from this general occupational approach, the FAIC system focuses on agricultural injuries alone, providing a trove of detailed information from which researchers can pull. The FAIC coding system was developed by the American Society of Agricultural and Biological Engineers (ASABE) to identify if fatalities or injuries related to farming/ranching are occupational (American Society of Agricultural and Biological Engineers, 2020). There are 10 FAIC codes, with four of them linked directly to North American Industrial Classification System (NAICS) codes. In addition to the above, the NORA location specifies the locale of the incident, and intentionality informs as to whether the incident was unintentional or intentional, such as in the case of workplace violence or a suicide.

The accuracy of the final data requires following the established coding rules closely, and performing quality checks. This permits for the aggregation of reports with other sources of data - essentially converting them to a common tongue and allowing different systems to "speak the same language.".

Whenever dual coding is part of the research process, it is important to mitigate variation between coders and to identify potential sources for error. Northeast Center (NEC) researchers developed an algorithm to identify AgFF injury in pre-hospital care reports (PCR) which, until this analysis, employed a dual coding protocol. The mechanics of the machine learning algorithm can be found in previous publications (Hirabayashi, Scott, Jenkins, & Krupa, 2020; Scott, Hirabayashi, Levenstein, Krupa, & Jenkins, 2021). To test the accuracy of classifications by different coders, two types of analysis were conducted: the use of Kappa scores on the first tier of coding, followed by percent level of agreement for the following tiers; the accepted approach when coding categorical data (Landis & Koch, 1977). Gorucu et al. set out to determine levels of agreement regarding codification of the OIICS and FAIC classification systems (Gorucu, Weichelt, Redmond, & Murphy, 2020). They identified five themes in regards to accurate coding of these systems: (a) inclusions/exclusion based on classification system, (b) inconsistent and/or discrepant reports, (c) incomplete and/or nonspecific reports, (d) the effects of supplemental information on coding, and (e) differences in coder interpretation of code selection criteria. With the above in mind, the intent of this paper is to focus on coder interpretation, and describe methods for maintaining the quality of injury record coding for PCRs, while minimizing both time and costs expended in the codification of these surveillance systems.

2. Materials and methods

2.1. Description of dataset

The records used were from the 2011–2016 Maine and New Hampshire pre-hospital care reports (PCRs) that had been determined to definitely or possibly contain an injury or exposure related to the agriculture, forestry, or fishing (AgFF) industries. The validity of PCRs has been established in an international study through the University of Leeds, with a pooled specificity of 0.94 and sensitivity of 0.74 within multiple national databases. In plain language, this means that paramedics correctly excluded a diagnosis in 94% of patients, and correctly diagnosed a patient in 74% of all cases (Wilson, Harley, & Steels, 2018). The process of narrowing down the original dataset of 2,714,766 records to 29,099 records for visual inspection and assignment of AgFF case determination is described in a previous publication: *The Development of a Machine Learning Algorithm to Identify Occupational Injuries in Agriculture Using Pre-Hospital Care Reports* (Scott et al., 2021).

2.2. Classification systems

It is advantageous to use existing coding methods when developing a new system for injury analysis, as this allows others to access those systems for confirmation and further fine-tuning. The coding team applied four classification systems to the dataset: OIICS, FAIC, (both described previously) intentionality, and location. The coding team established a separate set of four codes to determine whether injury intentionality was: (1) unintentional injury; (2) intentional injury, self-inflicted; (3) intentional injury, inflicted by other; and (4) unknown. This simple classification allows researchers to easily identify and categorize violent injuries and deaths and self-harm. The National Occupational Research Agenda (NORA) Agriculture, Forestry, and Fishing Dictionary of Terms identified Location of Incident as one of the preferred categories to define specific characteristics of injuries occurring in production agriculture and support services (Agricultural, 2008:). There are 14 location codes, including but not limited to field/pasture, barn, milkhouse, and farm shop.

Table 1
Agreement thresholds.

Coding Variable		Options Per Variable	Statistical Test	Agreement Required for Future Single Coding
OIICS	Type of Event of Exposure	8*	Level 1: Cohen κ score	Level 1: 0.61
	Primary Source of Injury	10*	Level 2–4: Percent agreement	Level 2: 75%
	Secondary Source of Injury	10*		Level 3: 50%
	Nature of Injury	9*		Level 4: 25%
	Part of Body Affected	9*		
FAIC Code		10	Cohen κ score	0.61
Intentionality		4	Cohen κ score	0.61
Location		14	Cohen κ score	0.61

* For OIICS, the number of options listed per variable is for Level 1.

2.3. Coding interface and protocols

All four coding systems were imported into a Microsoft Access 2016 database, along with the 1,258 PCR records. A form was designed to allow a coder to review the information from the PCR record (narrative, date of birth, admit date, gender, dispatch reason, location, primary impression, and mechanism of injury) and easily assign OIICS, FAIC, intentionality, and NORA location of incident. Links to the online OIICS coding tree, the research team's surveillance manual, EMS abbreviations, and the FAIC code were embedded in the form.

The coding team consisted of nine Northeast Center staff members. The coders were trained by the surveillance team's principal investigator and research coordinator with an overview of the surveillance manual, the coding systems, the coding interface, and hands-on practice. The initial coders were paired into five teams, based on experience (veteran coder with new coder) and availability (number of records to code). Within each coding pair, one was designated as coder A and the other as coder B, which corresponded to the database form they were instructed to use. As a result, each coder within an assigned pair was coding independently of their counterpart. The coder pairs were assigned between 150 and 350 records, depending on their reported availability.

After completing 25 records, the coder pairs viewed and resolved discrepancies in their coding. If unable to agree on a resolution, the records with discrepancies were reviewed by the surveillance team as a whole. Space was provided on all forms for coders to enter comments or questions. The PI and research coordinator updated the surveillance user manual to reflect feedback from coders and reviewed the updates with the coders.

2.4. Guidelines for agreement levels

Before beginning analysis of interrater reliability, the research team established thresholds for coder agreement for these systems, which, if met or exceeded, would eliminate the need for dual coding in the future. The agreement thresholds are listed in Table 1. The Cohen κ score is considered the key statistics for measuring interrater reliability, as it controls for the possibility of chance agreement (Gorucu et al., 2020; Landis & Koch, 1977). Choosing 0.61 as the Cohen κ score threshold was based on Viera and Garrett's interpretation of Kappa (see Table 2) for categorical variables, with 0.61 as the lowest point of substantial agreement (Viera & Garrett, 2005).

The research team did not use the Cohen κ score for OIICS Levels 2–4 due to the high number of categorical options, as shown in Table 3; in situations such as these, where many response options may not be selected, the use of Cohen score loses its power (McHugh, 2012). In explanation, while OIICS Source Level 1 consistently has nine options, allowing for the use of a Kappa rating, Levels 2–4 have multiple options. For example, in Level 3 there are six possible branches with the Construction Machinery source, but only four choices with Agricultural machinery. As a result, percentage agreement was employed, which is the number of records where coders agreed divided by the total number of records reviewed. This protocol was approved by the Institutional Review Board of the primary institution.

Table 2
Viera & Garrett's Interpretation of Cohen κ Score.

Kappa Range	Agreement
< 0	Less than chance agreement
0.01–0.20	Slight agreement
0.21– 0.40	Fair agreement
0.41–0.60	Moderate agreement
0.61–0.80	Substantial agreement
0.81–0.99	Almost perfect agreement

3. Results

The results of the coding pairs can be found in Table 5, where kappa (κ) ranged from 0.2605 for secondary source, to 0.8494 for event and exposure. Comparisons between the coder choice and the final choice can also be found in Table 4. Agreement was almost perfect between the individual coders and the final coding choice for type of event or exposure, body part, and primary source of injury, and there was substantial agreement between the nature of the injury, intentionality, and NORA location.

Agreement beyond the first digit of OIICS coding was measured in percent agreement, and type of event or exposure, body part, and primary source of injury continued to meet high levels of accord when tested against the final coding, while the secondary source of injury and the nature of the injury were also high, as seen in Table 5. These scores were lower when comparing coders against each other, as shown in Table 6, with the highest levels of agreement occurring in source of injury, secondary source, and event exposure.

Individual coder accuracy ranged from medium to high levels of agreement. As shown in Table 7, Kappa scores reached perfect levels of agreement between some coders in nature of injury, source and secondary source, and event exposure; though one coder only scored fair agreement regarding secondary sources of injury. These levels of agreement continued into the 2nd, 3rd, and 4th digits, with primary and secondary sources of injury and event exposure maintaining high percentages of agreement throughout. Confidence intervals were all in the positive direction with the exception of FAIC codes.

4. Discussion

It is reasonable to assume that the accuracy of some variables is more critical to successful public health interventions than others. For example, knowing the primary source of injury and the type of event and exposure are important in our ability to improve safety.

Table 3
Number of options available for OIICS Levels 2–4.

	Event/Exposure Type	Source of Injury	Nature of Injury	Part of Body Affected
Level 2	48	78	40	45
Level 3	178	439	192	91
Level 4	304	1139	375	74

Table 4
Comparing Coder versus Coder / Coder vs Final Coding.

	Comparing Coder A vs Coder B			Comparing Coder vs Final Coding		
OIICS (1st digit)	N	Kappa	95% CI	N	Kappa	95% CI
Nature of Injury	1258	0.5727	0.5241–0.6212	2517	0.7653	0.7366–0.7939
Body Party	1250	0.7479	0.7211–0.7748	2509	0.8536	0.8382–0.8689
Source of Injury 1	1258	0.7330	0.7042–0.7618	2517	0.8515	0.8353–0.8677
Source of Injury 2	1258	0.2605	0.2020–0.3190	2517	0.5198	0.4829–0.5566
Event Exposure	1258	0.8494	0.8271–0.8717	2517	0.9195	0.9075–0.9315
FAIC	1258	0.5346	0.4983–0.5708	2517	0.5939	0.5697–0.6182
Intentionality	1259	0.6052	0.4842–0.7261	2518	0.7395	0.6608–0.8181
NORA location	1257	0.5635	0.5321–0.5949	2516	0.7532	0.7344–0.7719

Table 5
Coder (A and B) versus Final Choice: % Agreement for OIICS codes beyond the first digit.

	Nature of Injury (n = 2517)	Body Part (n = 2509)	Source of Injury 1 (n = 2517)	Source of Injury 2 (N = 2517	Event Exposure (n = 2517)
2 digits	78.94	78.68	85.66	82.48	87.41
3 digits	74.29	71.26	82.80	82.08	81.17
4 digits	70.56	70.67	76.52	81.33	75.29

Table 6
Coder A versus Coder B: % Agreement for OIICS codes beyond the first digit.

	Nature of Injury (n = 1258)	Body Part (n = 1250)	Source of Injury 1 (n = 1258)	Source of Injury 2 (N = 1258)	Event Exposure (n = 1258)
2 digits	62.80	63.12	74.48	79.65	76.79
3 digits	54.93	50.16	70.35	78.78	65.58
4 digits	49.28	48.96	59.86	76.79	54.29

Table 7
Coder range of agreement.

	KAPPA	95% CI	2 digit agreement (%)	3 digit agreement (%)	4 digit agreement (%)
Nature of Injury	0.5818–1	0.5971–1	54.09–91.17	44.03–86.93	38.99–84.10
Body Part	0.7986–0.9411	0.4563–1	66.03–88.69	56.41–84.45	55.13–83.75
Source of Injury 1	0.6904–1	0.6040–1	71.52–89.40	62.66–88.34	51.90–83.75
Source of Injury 2	0.2987–1	0.1343–1	80.44–87.28	79.34–87.28	77.13–87.28
Event Exposure	0.8517–1	0.7897–1	79.25–100.00	70.44–100.00	55.97–100.00
FAIC	0.3149–0.8811	−0.0522–1			
Intentionality	0.5687–0.8203	0.1303–1.0000			
NORA location	0.6475–0.8160	0.3237–1.0000			

Public health interventions often target these two factors through a variety of ways, be it elimination, substitution, engineering controls, administrative controls, or personal protective equipment. An example would be data indicating tractor (source of injury) rollovers (event or exposure) being a significant cause of injury, and an intervention targeting the installation of rollover protective structures. Though possible, interventions do not typically target a specific nature of injury (e.g., preventing leg fractures, but not leg crushing), therefore those variables, while helpful in fully understanding the burden of injury, are not always critical for intervention development. Near perfect agreement for event and exposure, primary source of injury, and body part, along with the substantial agreement for nature, location, and intent, gives the research team confidence in changing the surveillance system protocols to eliminate time-consuming dual coding. When disagreement did occur, it was typically not wildly disparate, but more to do with the ordering of an injury event or noting the many rules within the OIICS system. It is worth noting that, due to its infrequent use, there was greater variation in the kappa score for secondary source of injury. Given that secondary source is not frequently assigned, this is not a critical value in the decision to change from dual to single coding. FAIC Coding showed moderate agreement between coders and the final choice. This is an area where additional guidance and training has been warranted. Our ability to draw distinctions between production agricultural injury events, which are likely captured in systems such CFOI or SOII (for larger events), from bystander injures, such as children hurt on the farm, is important. The blurring of the farm as often a workplace but often a home necessitates a means to code beyond traditional definitions of "work" to capture true risk. These findings mirror the kappa scores and general suggestions of Gorucu et al. (Gorucu et al., 2020).

These analyses allowed us to assess and customize additional coder training. Without the rigor of dual coding, there will be continued need for quality assurance checks. These should involve the senior members of the research team visually inspecting a random sample of coded cases on a routine schedule, to ensure that data quality is maintained. In addition, we recommend that a coder training environment is established, where they can practice and get feedback on their kappa scores and percent agreement, before coding new data. These proposed protocols could be applied to a variety of surveillance systems, especially when there is a concern to reduce the staff-time involved in running the system, without sacrificing data quality.

Various limitations presented themselves over the course of this project. It was necessary to train reviewers in assigning codes, and some developed a more firm understanding of the principles behind the coding than did others. Further, it is natural for code selection to drift as one becomes more familiar with the subject matter, albeit ideally in the direction of increasing accuracy. At other times, the narratives themselves represented a limitation, as not all information necessary for OIICS coding was always present. In these cases, there is a tendency to make assumptions that may not be borne out by the available information; for example, assuming an injury was unintentional when the narrative does not contain the details necessary to determine that status. A further limitation is that the diagnosis offered by an EMS PCR does not always match the final diagnosis as settled upon by the attending hospital physician, particularly in regards to diagnosis sensitivity (Wilson et al., 2018). While still effective in tracking AFF occupational injuries, the OIICS coding might differ somewhat if hospital records were incorporated alongside EMS PCRs.

5. Conclusions

This research provides for evidence-based decision making for customizing an occupational injury surveillance system, ultimately making it less costly. The quality of the coded data was acceptable for variables important for injury epidemiology and intervention development. Good stewardship of public health resources is critical for the long-term success of such programs, and continued refinements and cost-savings should be considered an important part of the system.

5.1. Practical applications

Assessing the rigor of occupational injury record coding provides critical information to tailor surveillance protocols, especially those targeted to make the system less costly. System administrators should consider evaluating the quality of coding, especially when dealing with free-text narratives before deciding on single coder protocols. Further, quality checks should remain a part of the system going forward.

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