**An approach for using population attributable fraction to analyze the health benefits of eliminating toxic chemicals**

Abstract

For over two decades, toxic use reduction (TUR), a form of source reduction, has successfully reduced or eliminated toxic chemical use in several industries. However, the occupational health benefits of eliminating toxic chemicals have rarely been studied, although TUR interventions are increasingly used. The aim of this study is to develop and present a framework for analyzing the health benefits of TUR interventions. The feasibility of the framework is tested with two case studies.

The first case study estimated that a proposed policy to ban the use of Trichloroethylene (TCE) in industrial vapor degreasing in the U.S could prevent five kidney cancers among workers and seven kidney cancers among bystanders, with savings of about $36 million. The second case study estimated that a new policy to prohibit the use of per[chloroethylene](https://www.wikiwand.com/en/Tetrachloroethylene) (PERC) for dry cleaning in the U.S could prevent about four bladder cancers among dry cleaning workers and could save about $9.2million.

This paper demonstrates that the proposed method can be used to estimate the health benefits to workers when toxic chemicals are eliminated and safer chemical alternatives are substituted. This approach enables health benefits to be estimated without onsite monitoring data and economic value of the estimated health benefit. Although there are limitations to using PAF,,it is a useful tool for estimating health benefits and can be used in making decisions about chemicals policies that affect environmental and occupational health.

Introduction

There is a growing agreement that our social, economic, and physical environments have a significant impact on public health (Council, 2011). According to the American Public Health Association (APHA), many public health issues do not have just one causal determinant, but rather are caused by multiple determinants that are related to public policy (APHA Policy Statement 2012). Therefore, promoting public health and safety by reducing exposure to such risks requires a significant governmental role for regulatory intervention (Hutton, 2000). Several such regulations have been enacted, covering a wide range of activities such as improving air and water quality; cleaning up hazardous sites; and reducing exposures to toxic chemicals from work or consumer product (Miller et al., 2006).

Commonly, regulatory decision making requires estimating the benefits of the proposed regulation. Informed analysis of the benefits and costs might help policy makers decide “whether particular interventions merit the expected costs associated with achieving these benefits and informs their choices among alternative strategies” (W. Miller, Robinson, L. A., Lawrence, R. S., & Institute of Medicine 2006). For instance, Executive Order 12866 of 1993 (Clinton 1993) requires a regulatory impact analysis for evaluating risks, benefits, and costs of proposed or existing regulations that have an annual impact on the economy of $100 million or more (National Research Council 2002).

### In the context of such regulations, possible health benefits of a regulatory intervention are evaluated and reported. For example, the [US Environmental Protection Agency](https://www.epa.gov/) (EPA) reported several health benefits in its analyses of the U.S. Clean Air Act (CAA) Amendments of 1990 (EPA, 1990). The EPA later developed a model (BenMap) to estimate the health benefits of decreasing exposure to ozone (Hubbell et al. 2005; U.S. EPA 2008b) and air-borne particulate matter PM2.5 (Davidson et al. 2007; Fann et al. 2011). The U.S. Centers for Disease Control and Prevention (CDC) also conducted various health benefit analyses, including studies of the effects of transportation policies on several chronic diseases (**Whitfield** **GP** et al., 2016), the effects of parking policies on obesity (Blanck HM et al., 2012), and the effects of school policies on children’s walking (W**endel AM et al., 2009)**.

### Health benefit assessments are helpful not only for governments. Several organizations have also developed methods for estimating the benefits of environmental health interventions. The World Health Organization (WHO) developed a comparative risk assessment methodology as a health benefits analysis for its Global Burden of Disease (GBD) project (Murray & Lopez, 1999). GBD is the one of the world’s most important efforts to measure the health effects of various diseases and injuries as well as the risk factors associated with them (Nelson et al., 2005). Similarly, the Institute of Medicine established a health benefits analysis tool to assess environmental health burdens and costs in the U.S (Trasande et al., 2015). Both methodologies are based on a population attributable fraction (PAF), but the estimated results (health benefits) are different because each method uses a different unit for health benefit.

Technically, health benefits analysis has used elements from other types of analysis, such as regulatory impact analysis, health impact analysis, and cost-benefit analysis. Each type of analysis uses a distinct model or focuses on specific health outcomes, depending on the specific purpose of the analysis. Therefore, several terms about health benefits analysis are used. In this study, if any analysis estimates any kinds of health benefit, we use the term “health benefits analysis” to avoiding confusion.

Health benefit analysis is widely used to assess the health impacts of a broad range of policy changes and health interventions. However, it has been used to analyze relatively few health benefits of environmental and occupational health interventions (Hutton, 2000). Moreover, the health benefits to workers from Toxic Use Reduction (TUR) policies have rarely been studied, although TUR interventions are increasingly conducted in the U.S. Therefore, there is a serious knowledge gap in understanding the total benefits of TUR policies. This may lead to an underestimation of the value of TUR interventions and may be an obstacle to expanding TUR policies.

This paper aims to describe and test a new framework based on the PAF for estimating the health benefits of TUR strategies. The framework was applied to two case studies to understand the feasibility, advantages and limitations of using this methodology in future analyses. Specifically, the two case studies discussed in this paper evaluate the possible health benefit and economic value due to the EPA proposing a policy to ban the use of TCE in industrial vapor degreasing in U.S and policy to prohibit the use of PERC in dry cleaning in U.S.

Method (The context of Health Benefit Analysis for TUR policy)

In 1918, the Institute of Medicine (IOM) established a general approach to assessing the “fractional contribution” of the environment to the causation of illness in the United States (Institute of Medicine Committee for a Planning Study on Ongoing Study of Costs of Environmental-Related Health, 1981). PAF is defined as “the proportion of the disease or health-related event that would be prevented in the population if the risk factor was eliminated” (Powles, Zatonski, Vander Hoorn, & Ezzati, 2005). The IOM method uses the PAF to identify the relationship between chemical exposure and health outcome.

 PAF has been useful in public health prevention policy since it assumes complete elimination of exposure (de Rezende & Eluf, 2016; Rockhill, Newman, & Weinberg, 1998). TUR policy also emphasizes prevention through the complete elimination of exposure. Therefore, the IOM’s health benefits analysis model was modified to be appropriate for studying the health benefits of TUR policies. This framework for analysis was then applied to two case studies. These cases were carefully chosen from a number of TUR case studies. The two case studies were selected because they used technologies that entirely replaced the use of toxic chemicals in the workplace.

The original IOM method was modified to enable practitioners or TUR planners to evaluate both the health and economic benefits of replacing toxic chemicals. The six steps of the health benefits analysis are described below and illustrated in Figure 1.

1. Step 1: Characterization of exposure scenario

The first phase of the analysis was a characterization of the exposure scenario for the TUR intervention. Exposure scenarios help to assess exposure, dose, and risk; it includes facts, data, and assumptions about how the exposure takes place (Agency, 2004). Therefore, target exposure, possible pathways, and health outcomes for benefits analysis were considered in the exposure scenario. In practice, many industrial chemicals are used at the same facility or in the same process, but TUR policy usually focuses on a priority chemical for an effective intervention, based on the chemical’s toxicity or the feasibility of using a safer alternative (Ellenbecker & Geiser, 2011). Therefore, it was a necessary to identify a target chemical

1. Step 2: Estimation of target population and prevalence of exposure

The second step of the analysis consists of estimating the size of the target population and the prevalence of exposure. The health benefits analysis determines the target population to indicate a distribution of impacts (W. Miller, Robinson, L. A., Lawrence, R. S., & Institute of Medicine 2006; OECD, 2006). In the same way, target populations affected by TUR policy are also estimated in consideration of the exposure scenario. Assured government census DB is widely used to indicate the number of the target population.

 For estimating the general population, U.S. Census data is publically available; it is commonly used for risk assessment or health benefits analysis of air pollution or hazardous waste sites (Agency  2009; Agency 2011; Agency  2015). For the occupational population, the Occupational Employment Statistics (OES) program and the Current Population Survey (CPS) from the Bureau of Census for the Bureau of Labor Statistics are also commonly used. It provides a broad range of demographic employment and other labor force information (Husain, Kalinin, Truong, & Dinov, 2015).

However, it is sometimes not possible to use these databses since certain target population data were not included. In these cases, target population data can be estimated using previous studies. For example, EPA used a 1997 survey to estimate the number of workers and bystanders potentially exposed to TCE This is still assumed to be the best estimate (Agency  2014).

Once the size of the target population is estimated, the prevalence of exposure is estimated for calculating PAF. There are two ways to estimate the prevalence of exposure. The first way is a direct survey. This might lead to more accurate results, but it requires time and effort and is therefore costly (Fritschi et al., 2016; Mittleman, 1995). The second way is to use publicly available databases or previous studies. In Canada and the EU, the national surveillance databases (CAREX Canada and CAREX EU) are used to estimate the prevalence of chemical exposure in workplaces and the environment (Peters, Ge, Hall, Davies, & Demers, 2014). However, the prevalence of exposure in the U.S might be different from those countries since each country has different working conditions and economic structures. For the case studies described below, previous studies and public surveillance databases were used to estimate the prevalence of exposure, rather than direct surveys.

3) Step 3: Estimation of the relationship (relative risk) between exposure and health outcome

In this step, the relative risks of health outcome (disease or injury) associated with the risk factor (exposed or used chemical) were measured through comprehensive review of the epidemiological literature. There is inherent uncertainty and variability in the relative risks identified across studies. Thus, it was important to select well-designed and conducted epidemiology studies. This was done by systematically reviewing the literature, applying criteria, and performing meta-analysis to compute summary risk estimates that provide more precise conclusions than previous studies (Haidich, 2010).

1. Step 4: Estimation of the population attributable fraction (PAF)

The PAF was calculated using the prevalence of an exposure and the relative risk of disease associated with exposure; it was estimated according to the following equation (Rockhill et al., 1998):

**PAF = Prevalence Exposure** × **(RR-1) / [ 1+(Prevalence Exposure** × **(RR-1))]**

The term “ RR” is the relative risk of disease or injury associated with the exposure.

5) Step 5: Estimation of health benefit (attributable health burden)

 The Institute of Medicine provided a method for calculating the attributable disease burden using the PAF in 1981(Institute of Medicine Committee for a Planning Study on Ongoing Study of Costs of Environmental-Related Health, 1981; Trasande et al., 2015). In this study, we considered the attributable disease burden as a health benefit since t chemical exposure would be prevented due to complete elimination of exposure. It was estimated using the following equation:

**Health Benefit (Attributable Disease Burden) =Disease rate** × **Population Attributable fraction (PAF)** × **Population size**

Disease rate refers to either the incidence or prevalence of a health outcome from the exposure scenario. Moreover, the size of the population was the estimated target population that would be affected by TUR policy.

6) Step 6: Estimation of the costs of health benefits (attributable costs)

The Institute of Medicine also provided a way to calculate attributable costs using the PAF. We calculated the costs of health benefits. using that equation

**Cost of health benefit (Attributable Costs) = Disease rate** × **PAF** × **Population size** × **Cost per case**

In this study, the term “case” was used for both fatal and non-fatal diseases. If a disease such as cancer could be either fatal or non-fatal, we used the survival rate to categorize the rate of fatal and non-fatal disease. For example, if there are 100 leukemia cases and the literature indicates that leukemia has a 60% survival rate, we assumed that 40 cases of leukemia are fatal and 60 cases are nonfatal. Then, the economic values of fatal and nonfatal diseases were estimated based on EPA guidelines for economic analysis.

The EPA guidelines for economic analysis recommend, using the default value of statistical life (VSL) for the cost of a fatal disease. VSL is a summary measure of the dollar value of small changes in mortality risk among the public (Agency  2016). The EPA currently recommends a default VSL of $7.9 million (in 2008 dollars) to reduced mortality for all programs and policies. This VSL was updated from the $4.8 million ($1990) estimate using the GDP deflator inflation based on the Consumer Price Index (CPI). We adopted the recommended VSL and adjusted the value from $7.9 million in 2008 dollars to $8.9 million in 2017 dollars. The U.S. CPI calculator was used, with a 13.2 % cumulative rate.

For nonfatal diseases, the EPA prefers to use the value of willingness to pay (WTP), but cost -of illness (COI) values are also accepted. However, there is uncertainty when default WTP represents the economic value of each specific nonfatal disease (EPA, 2000). Therefore, we only used the estimated cost of treatment (direct medical cost) for the economic value of nonfatal disease from EPA's Cost-of-Illness Handbook (Toxics, 2007). Note that the estimated cost in this case study might be underestimated compared to rather than WTP for nonfatal diseases.

Result (case studies)

This section describes the results of the two case studies, using the framework developed for analyzing the health benefits of TUR policies). We describe each case study’s possible exposure scenario and background based on existing or proposed TUR policies for toxic chemicals in the U.S.

Case study 1: Health benefits and costs of a proposed EPA policy to ban the use of TCE in industrial vapor degreasing.

Trichloroethylene (TCE) is considered a well-known carcinogen and is associated with adverse effects on the liver, kidneys, and immune system {Scott, 2011). Although there is grave concern about its high toxicity, TCE is still widely used in metal degreasing facilities. Recently, EPA proposed banning the use of TCE in industrial vapor degreasing, based on health risks identified in previous studies (EPA, 2016). In this case study, we used the health benefits analysis to estimate the ptential health benefits of the proposed EPA ban.

1. Characterization of exposure scenario

TCE is generally used for metal degreasing in industrial processes. EPA found that the main exposure pathway of TCE is inhalation, due to TCE’s high vapor pressure (Agency  2014). Dermal exposure might account for about 1% of total TCE exposure (Tibaldi, ten Berge, & Drolet, 2014), but this case study did not consider dermal exposure and considered only on exposure through inhalation. We assumed that there would be no TCE exposure after implementing the proposed policy in all US commercial vapor degreasing facilities. That is, all will have switched their degreasing solvents to safer alternatives.

Since this case study aimed to estimate occupational health benefits, the target population was workers and bystanders at metal degreasing facilities. The target health outcome was kidney cancer since there is strong evidence for a causal relationship between TCE and kidney cancer (Chiu et al., 2013). Thus, we estimated the health benefits and costs the proposed policy by estimating kidney cancer from TCE inhalation exposure for workers and bystanders at metal degreasing facilities.

1. Estimations of the size of the target populations and the prevalence of exposure

In 2006, EPA conducted risk assessments for halogenated solvents, including TCE. The study estimated the total number of degreasing facilities to be approximately 1,900 (EPA, 2006). This included 154 large industrial facilities and 1,746 small-medium industrial facilities. In a 2014 EPA risk assessment (EPA, 2014), it was estimated that 5 workers per facility and 12 occupational bystanders per facility were exposed to TCE. Based on these estimates, we estimated a target population for this study of 9,500 employees and 22,800 occupational bystanders at industrial vapor degreasing facilities. e Also, according to the EPA risk assessment, at least 90 % of the degreaser used was TCE (Agency  2014). We used this rate for prevalence of exposure and therefore assumed that 90% of the target population (workers at vapor degreasing facilities) was exposed to TCE.

3) Estimation of the relationship between exposure and health outcomes

The association between TCE and kidney cancer was assessed through a comprehensive review of the epidemiological literature (Scott & Jinot, 2011). The research used meta-analysis of well-designed studies for a quantitative evaluation of the evidence for associations between TCE exposure and kidney cancer(Scott & Jinot, 2011).

For the overall TCE exposure group of both workers and occupational bystanders, the evaluation showed a summary relative risk (RRm) of 1.27 (95% CI: 1.13, 1.43).. We assumed that workers were the higher exposure group and estimated the relative risk for workers only to be , 1.58 (95% CI: 1.28, 1.96) (Scott & Jinot, 2011).

4) The population attributable fraction (PAF) in the exposure scenario

We estimated the PAF between TCE and kidney cancer based on the assumption that TCE accounts for 90 % of the degreasing solvents used in industrial vapor degreasing. The estimated PAF for workers was 0.34 (95% CI: 0.2, 0.46) and 0.2 (95% CI: 0.1, 0.26) for bystanders. This suggests that 34 % of kidney cancer among workers and 20 % of kidney cancer among bystanders at vapor degreasing facilities could be prevented if TCE were removed.

5) The estimation of health benefit (attributable health burden) due to the EPA’s proposed policy

 In 2014, the Surveillance, Epidemiology, and End Results (SEER) Program of the National Cancer Institute estimated that about 483,225 people were living with kidney cancer in the United States (NCI, 2014). According to the U.S. Census, the estimated total U.S. population was 323,127,513 in 2016 (US census, 2016). Based on this datarecord, the estimated prevalence of kidney cancer in the U.S was 0.0015. Using this estimated prevalence, we calculated the health benefits for workers and bystanders using the equations described in Table 1.

In conclusion, we found that about 5 kidney cancers among workers and 7 kidney cancers among bystanders at industrial vapor degreasing facilities could be prevented by a proposed EPA policy to ban the use of TCE in such facilities.

6) Estimation of the economic value of health benefits due to the EPA’s proposed policy

The avoided costs of the health benefits (avoiding kidney cancer) were assessed using assumptions that depend on the probability that a case of kidney cancer will be fatal or nonfatal.. The 5-year survival rate was used to classify kidney cancer cases as either fatal or nonfatal.. According to the SEER program, the survival rate of kidney cancer was 74.1% between 2007 and 2013. Based on the survival rate, we estimated that about one fatal kidney cancer and four nonfatal kidney cancers among workers could be prevented with a TUR approach at metal degreasing facilities.

For fatal cancer, we applied the VSL to measure the economic value of lives saved. Since the current VSL is $8.9 million (2017 dollars), , the economic value of one avoided one fatal kidney cancer is about $8.9 million. For nonfatal cancer, the estimated medical cost of kidney cancer from EPA's Cost-of-Illness Handbook was used (Toxics, 2007). The direct medical cost was about $ 47,288 in 1984 dollars. We readjusted the value u. After readjusting for inflation (using the U.S. CPI inflation calculator, based on 13.2 % cumulative rate of inflation) this is about 0.1 million dollars ($113,138) in 2017 dollars. The economic value of four nonfatal kidney cancers among workers would thus be about 0.4 million dollars ($452,552). When the economic values of fatal and nonfatal cancers are combined, the EPA’s proposed policy could save about $9.3 million.

Using the same methodologies, we also calculated the economic the value of the health benefitsof the proposed EPA policy for bystanders The estimated cost of 2 fatal kidney cancers among bystanders is $17.8 million and the estimated cost of 5 non-fatal kidney cancers is $0.5 million ($565,690). Combining both costs, the economic value of health benefits for bystanders due to EPA’s proposed policy is about $18.3million. In conclusion, the total estimated economic value of health benefits due to EPA proposed policy is $36.1 million.

The detailed calculations of economic values of potential health benefits for workers and bystanders i are shown in Table 2

(Table 2)

Case Study 2: Health benefits and costs of a new policy to prohibit the use of PERC in dry cleaning in the U.S.

 Perchloroethylene (PERC) (also known as tetrachloroethylene or ethylene tetrachloride) is the most commonly used dry cleaning solvent in the U.S; more than 85% of U.S. dry cleaners use PERC as a cleaning solvent because it removes stains and dirt from all common types of fabrics (Guha N, 2012). However, in 2008, the Environmental Protection Agency (EPA) concluded that PERC should be classified as a "likely human carcinogen” based on evidence from epidemiological and animal studies (NPT, 1993). The International Agency for Research on Cancer (IARC) has listed PERC in Group 2A, “Probably carcinogenic to humans” (IARC, 1995).

Because of these adverse health impacts, PERC is more strictly regulated today than in the past, causing many dry cleaners to consider or use alternatives. For instance, in 2007, California banned the installation of new PERC dry cleaning machines and required the mandatory replacement of old machines until 2010. Moreover, California has banned all use of PERC for dry cleaning by 2023; EPA approved this law in 2011. Wet cleaning technologies are being used as an alternative to PERC for dry cleaning in Massachusetts (Onasch, J., 2011).

In this case study, we estimated the possible health benefits for dry cleaning workers and bystanders if PERC is prohibited for dry cleaning in the U.S.. This analysis could be used to inform decision making, as there currently are no federal laws or policies banning the use of PERC.

1. Characterization of exposure scenario

We examined exposure scenarios for dry cleaning employees in the U.S. Exposures to the public due to environmental releases of PERC from dry cleaning shops were not considered. Dry cleaning employees may be exposed to PERC while performing both everyday tasks and machine maintenance in dry cleaning facilities; they routinely breathe excessive amounts of PERC vapor and spill it on their skin (Agency, 2017; Guyton et al., 2014). Therefore, the possible exposure pathways in this case study are both inhalation and dermal exposure. TBladder cancer was selected as the target health outcome for analysis since increased bladder cancer cases among dry cleaners have been reported (Guha et al. 2010; International Agency for Research on Cancer (IARC) 2009). As a result, we estimated t of a hypothetical policy to ban the use of PERC.by estimating the health benefits and costsof bladder cancer due to occupational PERC exposure of workers in dry cleaning shops.

2) Estimation of the size of the target population and prevalence of exposure

The U.S. EPA estimated in 2006 that there were about 34,000 dry cleaner facilities nationwide and of these, approximately 28,000 suse PERC (Agency, 2006). For estimating the size of the target population, we used data from the Bureau of Labor (BLS) Statistics Database shows 110,640 workers in dry cleaning and laundry services in 2016.

Few studies have reported the prevalence of PERC exposure among dry cleaning workers. In 2008, the Halogenated Solvents Industry Alliance (HSIA) estimated that 70% of dry cleaners in the U.S used PERC as a solvent. Also, in 2010, Whittaker and Johanson found that roughly 66% of the dry cleaning machines in King County, Washington, used PERC as a dry cleaning solvent (Whittaker & Johanson, 2013). Based on these reports, we assumed that the prevalence of PERC exposure among dry cleaning workers was 70%.

1. The association between exposure and health outcomes using epidemiology studies

PERC is now considered a possible human carcinogen, based on animal and epidemiology studies. A recent review study from the International Agency for Research team on Cancer (IARC) found a significantly increased risk of bladder cancer (RR 1.47, 95% CI: 1.16 - 1.85) among dry cleaning workers (Vlaanderen J et al., 2014). This study was well conducted, using comprehensive review and meta-analysis of 26 selected studies. We therefore used the IARC study results to estimatethe PAF, based on exposure scenarios.

4) The population attributable fraction (PAF) for the exposure scenarios

Based on the collected information, we estimated the PAF in the exposure scenario (PERC exposure among dry cleaner with bladder cancer). PAF = 0.7 (1.47-1) / [0.7(1.47-1) +1] = 0.25

This means that about 25% of bladder cancersamong dry cleaning workers would be preventable if the PERC exposures were completely removed..

5) Estimation of the health benefits (attributable health burden) of a new policy to prohibit the use of PERC in dry cleaning in the U.S.

We used the incidence rate of bladder cancer among the general population to assess the attributable burden. According to the National Cancer Institute SEER program, the incident rate of bladder cancer was 19.5 per 100,000 people. Using the equation described above,, we calculated that the estimated attributable burden of bladder cancer is 3.64. This means that about four bladder cancers could be preventable by a policy to prohibit the PERC in dry cleaning.

6) The estimated economic value of health benefit (attributable costs)

The cost of health benefits (avoided bladder cancer) were separately assessed , depending on whether the cancer is considered fatal or nonfatal. The survival rate was used to make this determinationo According to the SEER program, the survival rate of bladder cancer was 76% between 2007 and 2013. Using this data, about 3 nonfatal bladder cancers and w 1 fatal bladder cancer were assumed for this study.

For 1 nonfatal bladder cancer, the estimated medical cost was used from EPA's Cost-of-Illness Handbook (Toxics, 2007). This was about $ 66,362 in 1991 dollars. Adjusted for inflation using the U.S. CPI inflation calculator, this is about $1.2 million ($1,200,201) in 2017 dollars. Therefore, the economic value of 4nonfatal bladder cancers among dry cleaning workers is about $0.33 million ($332,878).

We applied the VSL to estimate the economic value of a fatal bladder cancer, . Using the US CPI inflation calculator, we adjusted this to obtain a value of $8.9 million for 1 fatal bladder cancer that could be avoided by eliminating perc.

Combining the costs of both fatal and nonfatal bladder cancers, a policy to ban the use of perc in dry cleaning could avoid is about $9.2 million in costs.

Discussion / Conclusion

The PAF is commonly defined as ”the proportion of disease risk or incidence that could be eliminated from the population if exposure were eliminated” (Eide & Heuch, 2001; Levine, 2007) by implementation of public health policy. However, there are concerns about misapplication of PAF in health policy (Rockhill et al., 1998). For proper use, certain conditions should be met. First, the PAF assumes that exposure is entirely eliminated. Second, the relationship between exposure and disease is assumed to be causal rather than weakly associated. Third, the exposure is assumed to be an independent risk factor. This means that there are no confounding risk factors affecting the relationship between exposure and disease. If these conditions are not satisfied, the estimated PAF would be a meaningless value for health benefits analysis (Levine, 2007). Levine and Rockhill argue that in some previous studies of health policy, the PAF used did not meet these criteria and therefore led to unwarranted conclusions.

These conditions for using the PAF also apply to the framework described here, To comply with these conditions, health benefit model should only be used for TUR interventions or policies that eliminate a toxic chemicalat the source. Thus, it is necessary to check whether a TUR policy or intervention completely eliminates exposure to a target chemical at the source. In our case study, we assumed that a new policy to prohibit the use of TCE or PERC would eliminate any TCE or PERC exposure among workers. However, in practice, TUR interventions commonly reduce the use of toxic chemicals rather than completely eliminating their use. This is because of feasibility constraints, such as the economic burden of alternatives. This suggests a cautious interpretation of the estimated health benefits of TUR policies.y to reduce the usage of chemical using modified processing or administration intervention like training.

 The selection of the target chemicals and diseases is another limitation of this approach. The method investigates the health impacts of exposure and illness by reviewing published studies. However, there are serious knowledge gaps concerning the health effects of exposure to industrial chemicals. For example, only small portion of risk assessment including epidemiological studies among 85,000 chemicals have been performed and published (Villanueva et al., 2014; Wilson & Schwarzman, 2009). Publication bias may mean that studies showing no association between exposure and disease are not likely to be published. The lack of chemical-specific studies makes it difficult to collect relevant studies of industrial chemicals. (Villanueva et al., 2014). Therefore, there is a possibility that the health benefits analysis model cannot be used due to the lack of information on target chemicals or disease.

Moreover, there is uncertainty about the extent to which the health benefits and costs identified in a chosen epidemiology study indicate the relationship between the exposure and illness. Thus, it is critical to understand that the method was not designed to evaluatehealth benefits of one facility since each facility has distinct working conditions that might lead to different health benefits and costs. Conducting a comprehensive review before calculating a PAF or conducting additional uncertainty analysis is recommended..

In our case studies, we intentionally selected cases with only one target chemical used in the process. This simplified the analysis but in further TUR applications of this method, the interactions of various chemicals and how they might affect disease risks may need to be considered. A strength of our study is that we obtained our estimates of the causal relationship between exposure and diseases like TCE and kidney cancer through an extensive systematic review and meta-analysis. This minimized the chance of confounding and uncertainty in calculating the PAF.

In practice, most health or safety regulations, including TUR policies, frequently lead to more than one type of health benefit (W. Miller, Robinson, L. A., Lawrence, R. S., & Institute of Medicine 2006). For instance, a policy of banning TCE use could theoretically avoid lung cancer, malignant lymphoma, or immune disease, in addition to kidney cancer. However, the TUR framework presented here is only designed for a specific health outcome. Thus, health benefits from other type of illness could not be combined to understand the total health benefitsof the TUR policy. For the same reason, the TCE case study only estimated the number of prevented kidney cancers among workers. As a result, our model cannot estimate the total health benefits when several health benefits appeared through the same TUR intervention or policy.

On the other hand, some health economic analyses use summary health measures that combine different types of health effects into an integrated health unit (Agency  2016; W. Miller, Robinson, L. A., Lawrence, R. S., & Institute of Medicine 2006). For example, disability-adjusted life years (DALYs) and quality-adjusted life years (QALYs) are widely used health measures that combine different type of health impacts, including morbidity and mortality, into a single common unit (Gold, Stevenson, & Fryback, 2002). DALY and QALY are useful for overall estimates of the burden of disease and evaluations of the relative impact of specific diseases and injuries in economic analyses (Gold et al., 2002; Nelson et al., 2005).

 As a result, this model of health benefits analysis for TUR has the advantage of being relatively straightforward but may not be applicable when several types of health benefits are of interest (W. Miller, Robinson, L. A., Lawrence, R. S., & Institute of Medicine 2006). Further research would be needed to adapt summary health units for estimating the total health benefits of TUR policies.

The estimated economic value of health benefits in our model can be variable. We used U.S. EPA’s recommended VSL ($7.9 million in 2008 dollars) to estimate the economic value of avoiding the risk of fatal cancer from TCE or PERC exposure. However, the value of VSL differs, depending on the country. In 2014, the default VSL for OECD countries of USD (2005-USD) ranged from USD 1.5 million to USD 4.5 million, with a base value of USD 3 million. For the EU-27, the VSL range is USD 1.8 million – 5.4 million (2005-USD), with a base value of USD 3.6 million (OECD, 2014). Also, some studies indicated that default VSLs might under-estimate the value of a life since it does not include medical costs (US EPA, 2001). One study valued (avoiding fatal leukemia) from benzene exposure using a VSL that was adjusted for medical expenses (Agency  2009).

Tthe estimated economic value of non-fatal cancer was also under-estimated. Willingness to pay (WTP) is the preferred economic measure for health benefits of non-fatal diseases (Agency  2016). According to EPA guidelines for performing economic analyses, WTP is a maximum monetary amount that an individual or group would voluntarily pay to enjoy the benefits (or avoid the damages) from a policy change (Agency  2016; Martín-Fernández et al., 2010). It generally includes medical treatment costs, indirect costs such as lost time from work, and costs of emotional pain like discomfort or suffering (Freeman, 2003). However, rather than use WTP, we used only an estimatee of direct medical costs since there is significant uncertainty in using WTP for specific cancers from chemical exposure in the U.S.

Roughly, WTP is estimated in two approaches. The first method is a survey-based technique that asks selected population to state how much they would be willing to pay for the benefits. The second method relies on WTP research on other health outcomes or market data. For example, EPA converted a default VSLvalue to the economic value of non-fatal cancers in studying a policy to reduce carcinogens in drinking water (U.S. EPA 2005). However, in practice, the feasibility of measuring WTP is often limited. For example, conducting surveys requires time as well as human and financial resource. Also, there is uncertainty about transfering benefit values from related studies or market data to estimate a WTP value for other health outcomes or populations (Agency  2016). (Agency  2016).

If WTP is not available, the cost of illness is an accepted alternative in health research, with certain limitations. Thus, in this study, we used the direct medical costs of non-fatal cancer kidney and bladder cancers. ) This had the advantage of being relatively straightforward, but it could undervalue the costs. For instance, our value did not include the expenses of avoiding illness, indirect costs such as lost compensation from work, and emotional pain such as discomfort or suffering.

Although there were several limitations, this framework for health benefits analysis also has significant advantages.. First, this model was specifically designed to estimate the health benefit due to chemical elimination by TUR. In practice, only a few studies consider the possible health benefits of TUR. Those studies use lifecycle assessment LCA or alternative risk assessment (Youngblood, Dvorak, & Hawkey, 2008).

These studies were able to indicate the existence of health benefits from TUR, but they did not quantify them health benefits since LCA and P2OASYS do not examine the change in health impacts. Our study estimated the health benefits depending on the association between a specific chemical and related disease like cancer. Thus, the estimated health benefit was able to indicate the change of health benefit due to chemical elimination.

The second advantage of this framework is that the estimated health benefits was able to represent the health benefit among total workers at similar process or industry. The previous studies were conducted based on the one facility case information with exposure monitoring data (Kikuchi, Kikuchi, & Hirao, 2011). However, it is rare to measure the exposure level after TUR because there is no legal requirement to report (G. Miller, Burke, McComas, & Dick, 2008). Also, the estimated health impact or benefit based on the exposure data from one facility may not be generalizable to other facilities since each facility has different work environment and exposures.

In this study, the developed model used a systematic literature review instead of the one facility information from exposure monitoring data. Several published studies were reviewed and analyzed to estimate the association between same chemical and disease among workers at a similar process. Therefore, the result from the developed model can indicate the health benefit among the whole worker at similar industries or process over the result of one facility.

Third, the unit of estimated health from our model is easier to understand than other models and can transfer to the economic benefit. General risk assessment model evaluates a risk as a quantitative probability of harm to health and LCA models uses a single number like Disability-Adjusted Life Year (DALY) to indicate a health benefit. However, both quantitive units are difficult to interpret for the public, and the general public does not judge risk-based on numbers or statitstics alone (LIN, 2008).

Our model expressed the health benefits of a reduced number of specific disease patients among specific worker due to specific chemical elimination. It is a simple unit to understand. Moreover, the estimated health benefit can be monetarized. Therefore, the total health benefits from several diseases can be represented as an economic value since each estimated health benefit eventually converts to the same monetary unit like the US dollar. Estimated economic value is crucial for decision-making process since it is necessary to step to qualifying appropriate levels of investment (Buxton, Hanney, & Jones, 2004). As a result, the estimated health benefit through this model would be more accurate and understandable to the public than other methods like LCA or RA. Therefore, it may be a more useful tool for risk communication to the public and for policy decision making.

In this study, we provided the framework of health benefits analysis for TUR policy using the PAF from the Institute of Medicine. The outcome of our two case studies indicated that the developed method could estimate the health benefit and cost for the policies to ban the use of TCE for vapor degreasing and PERC for dry cleaning. The framework helps to understand not only the exposed risk but also quantifies the health benefit from toxic chemical elimination at the source. It provides a method to estimate the impact of past TUR interventions and this quantification of benefits may help to expand the reach of TUR policy in the future.

Further research, utilizing additional case studies, may be useful to test the developed framework of health benefits analysis from the reduction of industrial toxic chemical use. This method needs to expand to estimate the health benefit of the reduction of toxic chemical usage at the source. Furthermore, the method also needs to update the economic value of avoiding associated non-fatal disease; using the value of willingness to pay after comprehensive valuation review of WTP.

Although there are limitations to using PAF, this is a useful health benefit and decision-support tool to inform environmental or occupational chemical policy that promotes the switch from toxic chemicals to safer alternatives.

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Figure

Figure 1



Figure 1 the framework of health benefit analysis using PAF

Table

Table 1 the estimated health benefit due to the EPA proposed policy

Table 1 ) The estiamted health benefit (attributable health burden) due to the EPA proposing a policy

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Target Population | Prevalence Rate | PAF | Population Number(n) | Health Benefit |
|  |  |  |  |  |
| Worker | 0.0015 | 0.342 | 9,500 | 4.85 |
| Bystander | 0.0015 | 0.195 | 22,800 | 6.64 |
|  |  |  |  |  |

Table 2 the estimated economic value of health benefit due to the EPA proposed policy

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Target Population**  | **Health Benefit** | **Survival Rate**  | **Kidney Cancer Case (#)** | **Direct Medical Cost ($)** | **VSL ($)** | **Cost ($)** | **Total Cost ($)** |
| **Worker (non-fatal)** | 4.9 | 0.74 | 4.0 | 113,138 |  | 452,552 | 9,352,552 |
| **Worker****(fatal)** | 4.9 | 0.26 | 1.0 |  | 8,900,000 | 8,900,000 |
|  |  |  |  |  |  |  |  |
| **Bystanders (non-fatal)** | 6.6 | 0.74 | 5.0 | 113,138 |  | 565,690 | 18,365,690 |
| **Bystanders****(fatal)** | 6.6 | 0.36 | 2.0 |  | 8,900,000 | 17,800,000 |