**ABSTRACT**

**Background:** Quadrivalent influenza vaccines (QIVs) contain antigens derived from an additional influenza type B virus as compared with currently used trivalent influenza vaccines (TIVs). This should overcome a potential reduced vaccine protection due to mismatches between TIV and circulating B viruses. In this study, we systematically reviewed the available literature on health economic evaluations of switching from TIV to QIV.

**Areas covered:** The databases of Medline and Embase were searched systematically to identify health economic evaluations of QIV versus TIV published before September 2016. A total of sixteen studies were included, thirteen cost-effectiveness analyses and three cost-comparisons.

**Expert commentary:** Published evidence on the cost-effectiveness of QIV suggests that switching from TIV to QIV would be a valuable intervention from both the public health and economic viewpoint. However, more research seems mandatory. Our main recommendations for future research include: 1) more extensive use of dynamic models in order to estimate the full impact of QIV on influenza transmission including indirect effects, 2) improved availability of data on disease outcomes and costs related to influenza type B viruses, and 3) more research on immunogenicity of natural influenza infection and vaccination, with emphasis on cross-reactivity between different influenza B viruses and duration of protection.

**1. Introduction**

Seasonal influenza is a contagious acute respiratory infection, causing every year up to five million cases of severe illness and half a million deaths globally [1]. In addition, the economic burden of seasonal influenza is considerable. In the United States (US) for instance annual costs of US $10.4 billion in health-care utilization and US $16.3 billion in work absenteeism are caused by influenza [2]. Seasonal influenza can be caused by influenza type A viruses and influenza type B viruses. Although the majority of influenza cases are caused by influenza type A viruses (A/H1N1 and A/H3N2), the burden of influenza type B viruses has been shown to be substantial. Since 2001, two antigenically distinct lineages of influenza B viruses, B/Victoria (B/Vic) and B/Yamagata (B/Yam), circulate worldwide on an irregular basis, being responsible for 20–25% of all influenza cases [3–5].

To reduce seasonal influenza epidemics, most industrialized countries implemented influenza immunization strategies. Trivalent influenza vaccines (TIVs) contain antigens derived from two influenza A virus subtypes (A/H1N1 and A/H3N2) and one influenza type B virus (either B/Vic or B/Yam). Each year it is decided which influenza B lineage should be included, based on predictions of the World Health Organization (WHO) about the anticipated dominant influenza type B virus [1]. However, in the seasons 2001–2002 until 2010–2011, mismatches between the vaccine and the circulating B viruses have occurred in half of the seasons, while in some seasons co-circulation of both lineages was noticed [3]. Therefore, quadrivalent influenza vaccines (QIVs) have been developed and were first licensed in 2012 [6], containing strains of both influenza B lineages (B/Vic as well as B/Yam).

Currently, some countries already include QIV next to TIV in their vaccination recommendations, like the US, Canada, and Australia [7–9]. The United Kingdom (UK) extended the influenza vaccination program to children using the quadrivalent live-attenuated influenza vaccine (Q-LAIV) [10]. However, in many other countries, including most European countries,
TIV is still used because either QIV is not yet available, QIV procurement agreements with health-care providers might still be ongoing [11], or potential added benefits of QIV are not or not yet recognized by national immunization technical advisory groups (NITAGs).

A decision about switching from TIV to QIV is based on various criteria, of which a beneficial cost-effectiveness profile is often one of the principal aspects being considered by NITAGs in Europe [12]. Such cost-effectiveness assessments usually rely on mathematical models aiming to predict the impact of vaccination strategies on mortality, health-related quality of life, and costs to the health-care sector and society. In 2014, key issues and challenges relating to the determination of the impact and cost-effectiveness of quadrivalent influenza vaccination have already been described by Quinn et al. [13]. The authors recommended the use of subtype- and age-specific estimates of influenza disease burden and costs, because these estimates can differ between influenza A and B viruses across age-groups. Moreover, the existence of cross-protection from TIV against the unmatched B-lineage was discussed, potentially diminishing the relative impact of quadrivalent influenza vaccination. Finally, it was stated that the use of dynamic models would be important, as this modeling approach includes by definition indirect effects to the unvaccinated part of the population, which is of crucial relevance to the impact of vaccination.

To the best of our knowledge, two studies summarized the literature on the comparison of QIV versus TIV [13,14]. However, the corresponding searches seem not to be systematic. Moreover, a variety of economic evaluations of QIV versus TIV have subsequently been published. Therefore, we aimed to systematically review the literature on the economic value of QIV in order to analyze a potential switching from TIV to QIV, including the most recent publications. In addition, we aimed to identify gaps in the current knowledge and needs for future research.

2. Methods
2.1. Search strategy and study selection process
A literature search was performed in the Medline and Embase databases to identify relevant articles on the comparison of the health economic impact of QIV versus TIV that were published before 30 September 2016. Key words of the search included terms like influenza, quadrivalent, cost-effectiveness, cost-utility, cost-benefit, economic evaluation, and model. The full search strings can be found in the supplemental material and contained free text searching terms as well as controlled terms. We screened on titles and abstracts and eventually reviewed the full content of each eligible article. Also reference lists of eligible studies and review papers discussing the value of QIV were searched (snowballing).

Our selection criteria were that studies should contain original full economic evaluations of QIV versus TIV using a health-economic decision model. We considered studies of all age-groups and vaccine types. In order to be selected, studies had to include an economic comparison between QIV and TIV, or separately report outcomes for QIV and TIV that allowed calculation of this comparison by us. We limited our review to the English language. Abstracts of congress meetings, editorials, letters, and reviews were excluded.

2.2. Synthesis of results
The included papers were screened independently by two reviewers (BMvM and PTdB). First, the reporting quality of the studies was assessed using the Consolidated Health Economic Evaluation Reporting Standards (CHEERS) checklist [15]. Then, the following information was systematically extracted if possible/reported: (1) country of study, funding source, general characteristics of the analysis (type of analysis, model type, perspective, time horizon, currency and price year, discount rate, type of sensitivity analyses, and model validation performances); (2) target group and main features of the vaccination program (coverage and vaccine price) and vaccine characteristics (vaccine efficacy, level of cross-protection of TIV against the opposite type B virus, and duration of protection); (3) influenza-related characteristics (attack rate, details on outcomes, duration of immunity, influenza-related health effects, details on health-care costs, and work days lost); and (4) main study outcomes (reduction of influenza cases, reduction of influenza-related deaths, incremental cost-effectiveness/cost-utility ratios, and key drivers of cost-effectiveness outcomes). It is important to note that the terms cost-effectiveness and cost-utility are interchangeably used in this review. Reported model validation techniques were assessed using the AdVISHE, a tool containing a structured list of relevant items for validation [16]. This checklist includes five validation categories, that is, validation of the conceptual model, input data, computerized model, model outcomes, and ‘other’ validation techniques. Any model validation effort that was described in the economic evaluation was then extracted. To enhance comparability between studies, cost-outcomes were transferred to the 2015 price year using national consumer price indexes [17] and then converted to US $ using purchasing power parities [18]. If the costing year was not provided in the study, we assumed a costing year of ‘publication year minus 3 years.’ The reporting of our review was performed according to the PRISMA statement [19]. However, not all items of the PRISMA statement are applicable to economic evaluations.

3. Results
3.1. Study selection
The initial search in the databases of Medline and Embase resulted in a total of 49 studies, of which 35 remained after removing duplicates. Of these 35 studies, 2 studies were excluded after screening titles and abstracts, and from 18 studies no full-text was available as these referred to conference abstracts only. As one additional study that met our inclusion criteria was identified outside the initial search, we ended up with 16 eligible studies [20–35]. The flowchart of the study identification process is displayed in Figure 1. One study comprised a main paper and a corrigendum [27,36]. Of these 16 studies, 2 did not primarily focus on the cost-effectiveness of QIV as compared with TIV, but on high-dose TIV [21] or
adjuvanted TIV [29] as compared with TIV and QIV. However, as both studies reported detailed results of TIV and QIV, we included these studies in our review. Outcomes on QIV versus high-dose TIV or versus adjuvanted TIV were not included in this review, but are briefly described in the discussion section.

Overall, the reporting quality of the studies was found to be acceptable (see Table S1 for detailed scores per checklist item). A total of 13 out of 16 studies were ranked as good, adhering to more than 17 out of 24 items on the CHEERS checklist [20–26,28–31,33,35], while 3 studies were assessed as moderate, adhering to less than 17 out of 24 points [27,32,34]. Arguments for the choice of time-horizon and model-type were most often not reported. Also details on instruments used and populations involved to estimate the impact of influenza on quality-of-life were not presented in the majority of studies.

3.2. Study characteristics

A summary of the general study characteristics is given in Table 1. All studies were conducted in industrialized countries, including the US [21–23,27,29], UK [28,31,33], Canada [20,31], Spain [25], Finland [30], Australia [26], Germany [24], and Hong Kong [34,35]. One study analyzed the economic impact of QIV in 5 countries of the European Union (EU) and extrapolated this to all 27 EU countries [32]. Out of the 16 studies, 13 were funded by manufacturers [20–26,28–33], 1 was funded by public sources [27], and 2 studies were conducted without reporting any specific funding [34,35]. A total of 13 studies performed a cost-utility analysis [20–25,28–31,33–35], expressing results as costs per QALY gained. The remaining three studies conducted cost-comparisons [26,27,32].

Five studies used a dynamic modeling approach [23,24,29–31]. For three of these five studies, a more detailed description of the dynamic model was previously published [37–39]. Dynamic models simulate the transmission dynamics of influenza within the population and take into account age-stratified mixing patterns between different population groups, summarized in a ‘contact matrix.’ These models were compartmental SIR models (or extensions of such models), dividing the population between susceptible (S), infected (I), and recovered/immune (R), while adding a vaccinated compartment to account for those individuals protected by vaccination. By definition, dynamic models are able to account for both direct effects of vaccination and indirect effects on the vaccinated and the non-vaccinated population.
<table>
<thead>
<tr>
<th>Reference and country</th>
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<th>Type of analysis</th>
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<td>Chit [20], Canada</td>
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<td>1 season</td>
<td>CAD (2012), 5%/5%</td>
<td>Univariate, multivariate PSA</td>
<td>Cross-validation of model outcomes</td>
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<tr>
<td>Chit [21], United States</td>
<td>Industry</td>
<td>CUA</td>
<td>Static</td>
<td>Society</td>
<td>1 season</td>
<td>USD (2013), 3%/3%</td>
<td>Univariate, multivariate PSA</td>
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<tr>
<td>Clements [22], United States</td>
<td>Industry</td>
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<td>Static</td>
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<td>Dolk [24], Germany</td>
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<td>EUR (2014), 3.0%/1.5%</td>
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<tr>
<td>Garcia [25], Spain</td>
<td>Industry</td>
<td>CUA</td>
<td>Static</td>
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<td>Life-time</td>
<td>EUR (2014), 3%/3%</td>
<td>Univariate, multivariate PSA</td>
<td>Cross-validation of model outcomes</td>
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<tr>
<td>Jamotte [26], Australia</td>
<td>Public</td>
<td>CC (CCA)</td>
<td>Static</td>
<td>Payer and society</td>
<td>10 years (2002–2012, 2009 excluded)</td>
<td>AUD (2014), no discounting</td>
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<td>Meier [28], United Kingdom</td>
<td>Industry</td>
<td>CUA</td>
<td>Static</td>
<td>Payer and society</td>
<td>Life-time</td>
<td>GBP (2012/2013), 3.5%/3.5%</td>
<td>Univariate, multivariate PSA</td>
<td>Cross-validation of model outcomes</td>
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<tr>
<td>Mullikin [29], United States</td>
<td>Industry</td>
<td>CUA</td>
<td>Dynamic</td>
<td>Society</td>
<td>1 year</td>
<td>USD (NR), NA/3%</td>
<td>Univariate, multivariate PSA</td>
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</tr>
<tr>
<td>Nagy [30], Finland</td>
<td>Industry</td>
<td>CUA</td>
<td>Dynamic</td>
<td>Payer and society</td>
<td>20 years</td>
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<td>Univariate, multivariate PSA</td>
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<tr>
<td>Thonnnes [31], Canada and United Kingdom</td>
<td>Industry</td>
<td>CUA</td>
<td>Dynamic</td>
<td>Payer</td>
<td>10 years (following a 30-year burn-in period)</td>
<td>CAD (2013), 5%/5%, GBP (2013), 3.5%/3.5%</td>
<td>Univariate, multivariate, multivariate PSA</td>
<td>Face validity of input data, model fit testing, and cross-validation of model outcomes</td>
</tr>
<tr>
<td>van Bellinghen [33], United Kingdom</td>
<td>Industry</td>
<td>CUA</td>
<td>Static</td>
<td>Payer</td>
<td>Lifetime</td>
<td>GBP (2010), 3.5%/3.5%</td>
<td>Univariate, multivariate PSA</td>
<td>Cross-validation of the conceptual model and model outcomes, double programming</td>
</tr>
<tr>
<td>You [34], Hong Kong</td>
<td>No funding</td>
<td>CUA</td>
<td>Static</td>
<td>Society</td>
<td>9 seasons (2001–10, excluding 2009)</td>
<td>USD (2014), no discounting/3%</td>
<td>Univariate, multivariate PSA</td>
<td>Cross-validation of model outcomes</td>
</tr>
<tr>
<td>You [35], Hong Kong</td>
<td>No funding</td>
<td>CUA</td>
<td>Static</td>
<td>Payer and society</td>
<td>1 year</td>
<td>USD (NR), NA/3%</td>
<td>Univariate, multivariate PSA</td>
<td>Cross-validation of model outcomes</td>
</tr>
</tbody>
</table>

AUD: Australian dollar; CAD: Canadian dollar; CC: cost comparison; CCA: cost-consequence analysis; CUA: cost-utility analysis; EUR: Euro; GBP: Great British Pound; NA: not applicable; NR: not reported; PSA: probabilistic sensitivity analysis; QIV: quadrivalent influenza vaccine; TIV: trivalent influenza vaccine; USD: US dollar. *Uhart et al. [32] reported results of 5 European Union countries (EUS) (France, Germany, Italy, Spain, and United Kingdom) and extrapolations of these results of 27 European Union countries (EU27).
population, for example, herd protection or potential age shifts regarding incidence peaks [40,41]. The other 11 studies used static models [20–22,25–28,32–35]. Three of these 11 studies used the same Markov model [25,28,33] developed by van Bellinghen et al. [33], while 6 studies [20,21,26,27,32,34] followed and extended the approach that was explained in the online available spreadsheet-based model by Reed et al. [42]. All of the static modeling studies neglected indirect effects.

The societal perspective was the most considered perspective [20–30,32,34,35], including direct medical costs and indirect costs due to productivity losses. Other perspectives that were used concerned the payers perspective, comprising medical costs only [20,23,24,26–28,30–33,35]. Notably, some studies evaluated the decision problem from more than one perspective. Next to the perspective, the studies’ time horizons present a core issue, with the longer time horizon generally being preferred but requiring long-term data and/or additional assumptions. The time-horizon varied across studies from one year to a lifetime. Four studies performed a retrospective analysis in which the additional benefit of QIV was estimated over 10 influenza seasons [26,27,32,34]. In some dynamic models, the total analysis time is longer than the time horizon (i.e. evaluation period) because of a ‘burn-in’/’run-in’ period [23,24,30,31]. This burn-in period is used to allow the model’s dynamic behavior to settle down before the analysis between TIV and QIV is undertaken. For instance, in the study of Dolk et al. [24], each simulation ran for 40 years. The first 20 years were used for initializing age-dependent infection and immunity patterns in the population and the final 20 years for studying the intervention of QIV versus TIV.

All studies except one applied an equal discount rate for costs and health effects, ranging from 3% for the US [21,22,27,34,35], Finland [30], and Spain [25], to 5% for Canada [20,31]. Only the study for Germany used differential discount rates, that is, 3% for costs and 1.5% for health effects [24]. Three studies reported a discount rate for health effects only [29,34,35], as they limited discounting to life-years gained of influenza-related deaths. Two studies analyzing the impact of QIV retrospectively did not apply discounting [26,32].

To accommodate for uncertainty of relevant parameters in the model, most studies performed sensitivity analyses. A total of 13 studies performed a probabilistic sensitivity analysis (PSA) [20–25,27–31,33,35], 14 studies univariate sensitivity analyses [20–25,28–35], and 1 study a deterministic multivariate sensitivity analysis [31]. Descriptions on model validation were found to be scarce. The majority of studies performed cross-validation of the model outcomes to other studies [21–26,28–35]. Other reported validation efforts were double programming [33], face validity testing of the input data [31], and testing of the fit of the dynamic model to influenza incidence data [30,31]. In addition, Nagy et al. [30] reported that the temporal patterns of influenza incidence in Finland produced by the calibrated model were validated against Finnish national surveillance reports. For two studies, we did not find any model validation effort reported [20,27].

3.3. Characteristics of the vaccination programs and vaccines

Table 2 shows the characteristics of the vaccination programs/vaccines, used as main inputs for the models. Most studies focused on the whole population [20,22–24,27,29–33,35]. Two studies focused on the vaccination of the elderly aged ≥65 years [21,34], while three studies included elderly aged ≥65 years and people < 65 years with clinical risk conditions [25,26,28]. Vaccine coverage was predominantly based on current national uptake rates of the influenza vaccination program. Most studies focused on inactivated influenza vaccines only, while three studies also included a live-attenuated vaccine (LAIV) for age-groups where this vaccine is licensed [22,30,31].

All studies assumed equal vaccine efficacy of TIV and QIV against influenza type A viruses, as both vaccines contain the same influenza type A strains. Therefore, the vaccine efficacy against influenza A is not explicitly taken into consideration in this review. With regard to vaccine efficacy against influenza B, most studies used data from published meta-analysis by Tricco et al. [43] or DíazGranados et al. [44], while two studies [20,31] adopted the vaccine efficacy reported for the US vaccination program by Reed et al. [42]. Two studies did not differentiate between vaccine efficacy against influenza A and influenza B [24,29]. Almost all studies assumed that the vaccine efficacy of TIV against influenza B is proportional to the relative match with the circulating influenza B lineage in the last decade, with the match failing in approximately half of the seasons. In case of mismatched seasons, 11 studies assumed that TIV provides cross-protection against the mismatched influenza B lineage [20–24,26,28,31–34]. This level of cross-protection ranged between 60% and 70% of the matched vaccine efficacy. For QIV, studies predominantly applied the matched vaccine efficacy of TIV against both B-lineages. Chit et al. [21] increased the efficacy for 65+ year-olds from 49.0% for TIV to 50.7% for QIV. Four dynamic modeling studies reported information regarding the duration of the vaccine-induced protection [23,24,30,31]. Two studies set the average duration of vaccine protection at 1 year [23,31] and one study at 1.81 years [24] (presented in [39]). The study of Nagy et al. [30] used a probabilistic approach during the calibration process, sampling durations from a range of 0.5–3 years using a uniform distribution.

Figure 2 shows the incremental vaccine price of QIV over TIV. Seven studies based the vaccine price of QIV on published price lists [20,22–25,28,31], for instance, from the Centers of Disease Control and Prevention vaccine price list. Other studies assumed a hypothetical vaccine price for QIV [20,29,33,35], extrapolated the price increase from another country [31], or explored a range of vaccine price differences [27,34]. The incremental vaccine price varied considerably across studies, ranging from US $1.25 for Canada [20] to US $7.14 for the US [21]. Two studies assumed an equal vaccine price (price parity) of QIV and TIV [26,30], while the study of Uhart et al. [32] did not report vaccination costs, which, in interpreting their results, also reflects price parity between QIV and TIV. The three studies that included LAIV in their analysis...
<table>
<thead>
<tr>
<th>Reference and country</th>
<th>Included population</th>
<th>Vaccine type</th>
<th>Vaccine coverage (%)</th>
<th>Efficacy/effectiveness of TIV against influenza B (%)</th>
<th>Cross-protection of TIV against opposite B-lineage (%)</th>
<th>Efficacy of QIV against influenza B (%)</th>
<th>Incremental vaccine price (2015 US $)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chit [20], Canada</td>
<td>All ages</td>
<td>IV</td>
<td>0-19 y: 31.0, 20-49 y: 27.0, 50-64 y: 47.0, 65-74 y: 71.0, 75-84 y: 81.0, ≥85 y: 78.0</td>
<td>Matched lineage: 47 %</td>
<td>Yes: 60</td>
<td>Matched efficacy of TIV against both B-lineages: 123</td>
<td></td>
</tr>
<tr>
<td>Chit [21], United States</td>
<td>Elderly (≥65 y)</td>
<td>IV (high-dose)</td>
<td>67</td>
<td>Unmatched lineage: 28 %</td>
<td>Overall influenza efficacy: 49.0</td>
<td>Yes: 60</td>
<td>Overall influenza efficacy: 50.7</td>
</tr>
<tr>
<td>Clements [22], United States</td>
<td>All ages</td>
<td>IV or LAIV market share for &lt;50 y</td>
<td>&lt;5 y: 47.2, 5-7 y: 21.3-18 to 49 y: 30.5, 50-64 y: 44.5, ≥65 y: 66.6</td>
<td>Matched lineage: 66-77%</td>
<td>No Matched efficacy of TIV against both B-lineages</td>
<td></td>
<td></td>
</tr>
<tr>
<td>de Boer [23], United States</td>
<td>All ages</td>
<td>IV</td>
<td>0-5y: 51.5, 2-4 y: 67.6, 5-10 y: 54.2, 11-14 y: 44.0, 15-18 y: 33.7, 19-49 y: 33.7, 50-64 y: 42.7, ≥65 y: 64.9</td>
<td>Matched: 49.2-80%</td>
<td>No</td>
<td>Matched efficacy of TIV against both B-lineages: 4.52</td>
<td></td>
</tr>
<tr>
<td>Dolk [24], Germany</td>
<td>All ages</td>
<td>IV</td>
<td>At risk: 0-5 y: 33.0, ≥65 y: 64.9</td>
<td>Matched lineage: 66-70%</td>
<td>Yes: 67</td>
<td>Matched efficacy of TIV against both B-lineages: 3.76</td>
<td></td>
</tr>
<tr>
<td>Garcia [25], Spain</td>
<td>All ages</td>
<td>IV</td>
<td>Healthy: 65-69 y: 28.4, 70-74 y: 49.6, 75-79 y: 48.2, 80-84 y: 64.6, ≥85 y: 57.6</td>
<td>Matched: 66-70%</td>
<td>Yes: 67</td>
<td>Matched efficacy of TIV against both B-lineages: 3.76</td>
<td></td>
</tr>
<tr>
<td>Jamorte [26], Australia</td>
<td>Elderly (≥65 y) and people 6 mo-64 y with clinical risk conditions</td>
<td>IV</td>
<td>At risk: 0-17 y: 41.3-18 y: 64 y: 36.2, ≥65 y: 74.6</td>
<td>Matched: 66-70%</td>
<td>Yes: 67-68</td>
<td>Matched efficacy of TIV against both B-lineages: Price parity</td>
<td></td>
</tr>
<tr>
<td>Lee [27], United States</td>
<td>All ages</td>
<td>IV</td>
<td>At risk: 25 %</td>
<td>No</td>
<td>Matched efficacy of TIV against both B-lineages: 5.16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Meier [28], United Kingdom</td>
<td>Elderly (≥65 y) and people aged 18-64 y with clinical risk conditions</td>
<td>IV</td>
<td>Healthy: 18-64 y: 0, ≥65 y: 71.1</td>
<td>Matched: 66-70%</td>
<td>Yes: 68</td>
<td>Matched efficacy of TIV against both B-lineages: 3.76</td>
<td></td>
</tr>
<tr>
<td>Mullikin [29], United States</td>
<td>All ages</td>
<td>IV (live)</td>
<td>0-3 y: 72.2, 4-6 y: 63.4, 7-9 y: 61.0, 10-19 y: 49.3, 20-49 y: 32.3, 50-64 y: 45.3, ≥65 y: 65.0</td>
<td>Overall influenza efficacy of 0.40-0.65%</td>
<td>NR</td>
<td>Overall influenza efficacy of high match season: 4.34</td>
<td></td>
</tr>
<tr>
<td>Nagy [30], Finland</td>
<td>All ages</td>
<td>IV</td>
<td>0.5-2 y: 22.9, 3-4 y: 28.1, 5-14 y: 24.0, 14-17 y: 22.9, 18-21 y: 12.0, 22-26 y: 0.91, 27-29 y: 10.9, 30-44 y: 13.0, 45-60 y: 18.0, 61-72 y: 40.9, ≥73 y: 70.1</td>
<td>Overall influenza efficacy of IV: 48-99%</td>
<td>No</td>
<td>Matched efficacy of TIV against both B-lineages: Price parity</td>
<td></td>
</tr>
<tr>
<td>Thommes [31], Canada and United Kingdom</td>
<td>All ages</td>
<td>IV</td>
<td>Canada: 0 y: 16.8, 1 y: 32.9, 2-11 y: 28.3, 12-19 y: 22.9, 20-34 y: 16.1, 35-44 y: 40.7, 45-64 y: 31.4, ≥65 y: 64.4</td>
<td>Matched: 66-70%</td>
<td>Yes: 68</td>
<td>Matched efficacy of TIV against both B-lineages: Canada: 2.87.</td>
<td></td>
</tr>
<tr>
<td>Uhart [32], EU-5 and EU 27</td>
<td>All ages ≥ 6 mo</td>
<td>IV</td>
<td>2-17 y: 72.6, 50-64 y: 45.3, ≥65 y: 65.0</td>
<td>Overall influenza efficacy of 0.40-0.65% in high match season and 0.25-0.56% in low match season</td>
<td>No</td>
<td>Matched efficacy of TIV against both B-lineages: Price parity</td>
<td></td>
</tr>
<tr>
<td>van Bellinghen [33], United Kingdom</td>
<td>All ages</td>
<td>IV</td>
<td>Healthy: 0-64 y: 0, ≥65 y: 71.2</td>
<td>Matched: 66-70%</td>
<td>Yes: 68</td>
<td>Matched efficacy of TIV against both B-lineages: 1.37</td>
<td></td>
</tr>
<tr>
<td>You [34], Hong Kong</td>
<td>Elderly (≥65 y)</td>
<td>IV (live)</td>
<td>Clinical risk conditions: 0-4 y: 17.2, 4-6 y: 44.5, ≥65 y: 71.2</td>
<td>Matched: 66-70%</td>
<td>Yes: 70</td>
<td>Matched efficacy of TIV against both B-lineages: 1.00-10.01</td>
<td></td>
</tr>
<tr>
<td>You [35], Hong Kong</td>
<td>All ages</td>
<td>IV</td>
<td>0-4 y: 28.4, 5-14 y: 11.0, 15-64 y: 10.3, ≥65 y: 39.1</td>
<td>Matched: 49.2-68.8%</td>
<td>No</td>
<td>Matched efficacy of TIV against both B-lineages: 3.10</td>
<td></td>
</tr>
</tbody>
</table>

allIV: adjuvanted inactivated influenza vaccine; IV: inactivated influenza vaccine; LAIV: live attenuated influenza vaccine; NA: not applicable; NR: not reported. 6Depending on age. 7Switch from trivalent LAIV to quadrivalent IV. 8Adopted from Eichner et al. [39]. 9Averaged over 10 seasons. *Results were derived from the corrigendum [36]. 10Depending on country.
used the same price for trivalent LAIV and Q-LAIV [22,30,31].
Vaccine administration costs were excluded in this review, as these costs are expected to be identical for TIV and QIV.

3.4. Influenza-related characteristics

Table 3 depicts an overview of the influenza-related input characteristics. An important epidemiological parameter concerns the probability to contract influenza among unvaccinated persons (attack rate). Half of studies reported this parameter [21,22,25–29,33]. In these studies, the probability of getting infected was age-dependent, being higher for children than for adults. Influenza cases were then split to subtype and lineage using laboratory data on influenza-positive tests. No distinction by age group was made in any study in the division of the influenza cases over influenza A and influenza B. Dynamic models estimated influenza incidence by subtype and lineage incidence by calibrating the model on time series of influenza-like illness incidences combined with laboratory data on influenza-positive tests [23,24,30,31]. Logically, studies with a dynamic modeling approach rather reported a basic reproduction number \(R_0\) than attack rates to demonstrate the spread of infection within the population. Notably, the \(R_0\) reflects the average number of secondary infectious individuals produced by an average primary infectious case in a totally susceptible population.

The number of influenza-related hospitalizations or deaths was mostly calculated by multiplying the number of symptomatic influenza cases with the age-specific probabilities of these events, while some studies applied event rates on the study population directly. Other studies [34,35] used a top-down approach similar to the model of Reed et al. [42], estimating the number of influenza cases by dividing national influenza-associated death rates with influenza case-fatality ratios from the literature. Three studies used outcomes data that were specific for influenza B [30,34,35]. Two studies from Hong Kong used influenza B-specific hospitalization rates and/or influenza B mortality rates [34,35], while Nagy et al. [30] adapted subtype-specific outcomes estimated from the UK to Finland. All other studies used the same outcome probabilities across all influenza subtypes.

The QALY loss per influenza illness is calculated using two main parameters, that is, the quality of life estimate of influenza disease (utility) and the duration of the associated episode. Most studies split the duration and utility for influenza in two different categories, that is, uncomplicated and complicated influenza infections (including hospitalization) [21,23–25,28,31,33–35], while three studies applied average estimates of influenza-related QALY losses directly from the literature [20,23,30]. One study ignored QALY losses due to influenza illness assuming the disease to be transitory with negligible impact on the overall quality of life, but included QALY losses due to mortality [22]. We found that all studies based their QALY estimates on published data from non-subtyped influenza cases; that is, no studies used data specific for influenza type B infection.

Influenza-related costs can be separated into health-care and non-health-care costs. The health-care cost includes predominantly GP costs, hospitalization costs, and drug costs, while non-health-care costs include costs for travelling and productivity losses due to work loss. Overall, we found that on average the studies for the US had higher health-care costs than the studies from other countries. With regard to productivity losses of influenza-associated deaths, five studies [24,27,28,30,35] used the human capital approach valuing productivity losses until the age of retirement (Table 3). Three studies [20,21,23] applied the friction cost methods, assuming that an employee falling out of the production process will be replaced by an unemployed person after a friction period and that a certain elasticity of labor time and production applies. Again, no studies used data on resource use or absenteeism that was stratified by influenza subtype.

A final important parameter of interest concerns the duration of protection after natural infection. This parameter was implemented in four dynamic modeling studies [23,24,30,31].
Table 3. Influenza-related input parameters of the included studies.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Annual influenza attack rate (%)/R₀</th>
<th>Proportion influenza B of total influenza circulation, proportion influenza B unmatched</th>
<th>Health effects influenza morbidity</th>
<th>Health effects influenza mortality</th>
<th>Work days lost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chit [20], Canada</td>
<td>NR</td>
<td>NR</td>
<td>QALY loss of 0.0146–0.0293³ per influenza case</td>
<td>Life-expectancy corrected for age-specific utility</td>
<td>Illness: NR</td>
</tr>
<tr>
<td>Chit [21], United States</td>
<td>≥65 y: 5.7</td>
<td>NR</td>
<td>Uncomplicated: utility of 0.25 for 60 days. Hospitalized: utility of 0.2 for 8.3 days</td>
<td>Life-expectancy corrected for age-specific utility</td>
<td>Mortality: friction period of 90 days</td>
</tr>
<tr>
<td>Clements [22], United States</td>
<td>&lt;5 y: 20.3, 5–17 y: 10.2, 18–64 y: 6.6, ≥65 y: 9.0</td>
<td>21%, of which 50% unmatched</td>
<td>Not included</td>
<td>Life-expectancy corrected for age-specific utility</td>
<td>No complication: 0.5–1 day.</td>
</tr>
<tr>
<td>de Boer [23], United States</td>
<td>R₀ B/Victoria: 1.10–1.77, R₀ B/Yamagata: 1.02–1.86</td>
<td>Intrinsic to calibration process</td>
<td>Uncomplicated: QALY loss of 0.005 for children and 0.007 for adults. Complicated: QALY loss of 0.042–0.076 for children and 0.013 for adults. Outpatient visit: disutility of 0.127–0.262 for 3.3–10.1 days³. Hospitalized: disutility of 0.38 for 3.3–10.1 days³.</td>
<td>Life-expectancy corrected for age-specific utility</td>
<td>Uncomplicated: 0.5–1 days⁵.</td>
</tr>
<tr>
<td>Doik [24], Germany</td>
<td>R₀: 1.575⁵</td>
<td>Intrinsic to calibration process</td>
<td>Uncomplicated: disutility of 0.32–0.465⁹ for 7.5 days. Outpatient complications: disutility of 0.32–0.465⁹ for 7.5 days. Inpatient complications: 0.54–0.60⁹ for 1.93–14.13 days⁹.</td>
<td>Life-expectancy corrected for age-specific utility</td>
<td>Uncomplicated: 0.5–1 days⁵.</td>
</tr>
<tr>
<td>Garcia [25], Spain</td>
<td>0–17 y: 19.2, 18–64 y: 6.55, ≥65 y: 6.17</td>
<td>25.7% of which 64.2% unmatched</td>
<td>Uncomplicated: disutility of 0.32–0.465⁹ for 7.5 days. Outpatient complications: disutility of 0.32–0.465⁹ for 7.5 days. Inpatient complications: 0.54–0.60⁹ for 1.93–14.13 days⁹.</td>
<td>Life-expectancy corrected for age-specific utility</td>
<td>Illness: NR.</td>
</tr>
<tr>
<td>Jamotte [26], Australia</td>
<td>6 mo–4 y: 18.8, 5–17 y: 16.5, 18–64 y: 3.6, ≥65 y: 4.9</td>
<td>24.8% of which 52.6% unmatched</td>
<td>No QALY loss.</td>
<td>No QALY loss.</td>
<td>NA</td>
</tr>
<tr>
<td>Lee [27], United States</td>
<td>Estimated combining age-specific influenza mortality rates with a case-fatality ratio⁴</td>
<td>23% of which 49.4% unmatched⁴</td>
<td>No QALY loss.</td>
<td>No QALY loss.</td>
<td>NA</td>
</tr>
<tr>
<td>Meier [28], United Kingdom</td>
<td>18–64 y: 6.6, ≥65 y: 6.2</td>
<td>25.7%, unmatched NR</td>
<td>Uncomplicated: Disutility of 0.68–0.88⁸ for 7.5 days (without antiviral treatment) or 5 days (with antiviral treatment). Complicated: disutility of 0.80–0.98⁸ for 14.3 days.</td>
<td>Life-expectancy corrected for age-specific utility</td>
<td>Illness: NR.</td>
</tr>
<tr>
<td>Mullikin [29], United States</td>
<td>0–4 y: 20.3, 5–17 y: 10.2, 18–64 y: 6.6, ≥65 y: 9.0</td>
<td>21.3%, unmatched NR</td>
<td>Uncomplicated: no QALY loss. Complicated: QALY loss 0.00904 to 0.10000³ to 0.10000³.</td>
<td>Life-expectancy corrected for age-specific utility</td>
<td>Illness: NR.</td>
</tr>
<tr>
<td>Nagy [30], Finland</td>
<td>R₀: 1.6–3.9</td>
<td>Intrinsic to calibration process</td>
<td>QALY loss of 0.0429 per influenza case</td>
<td>Life-expectancy corrected for age-specific utility</td>
<td>Uncomplicated: 1.56 days.</td>
</tr>
<tr>
<td>Thommes [31], Canada and United Kingdom</td>
<td>R₀ mean: 1.3, R₀ seasonal peak: 1.9</td>
<td>Intrinsic to calibration process</td>
<td>Canada: uncomplicated: QALY loss of 0.0041. Complicated: QALY loss of 0.0146–0.0293³</td>
<td>Life-expectancy corrected for age-specific utility</td>
<td>NA</td>
</tr>
</tbody>
</table>

(Continued)
3.5. Study outcomes

The effectiveness and cost-effectiveness results of QIV versus TIV are summarized in Table 4. We found that the impact of QIV on influenza-related morbidity and mortality varied considerably across studies. Overall, dynamic models reported higher reductions of influenza-related morbidity as compared with static models. The impact of QIV on the total number of influenza cases (type A and B) as compared with TIV ranged from a reduction of 0.15% in the US using a static model [22] to 6.47% in the US using a dynamic model [29]. Studies presenting results for influenza B only found reductions of 29.2% for the US using a dynamic model [23] and 14.7% for Hong Kong using a static model [35]. One study focusing on elderly in Hong Kong presented incidence rates of averted influenza B cases, finding a total reduction of 118–508 per 100,000 person years [34]. Impact on influenza-related mortality was generally estimated somewhat higher than influenza morbidity (Table 4).

Figure 3 shows the cost-effectiveness results of QIV versus TIV, expressed as incremental cost-effectiveness ratios (ICERs). From a payer’s perspective, a cost-effectiveness study for Finland [30] and cost-comparisons for Australia and the European Union [26,32] found that QIV would result in cost-savings (Figure 3A). However, these studies assumed price parity between QIV and TIV [26,30] or excluded vaccination costs in their analysis [32]. The highest ICER was found by Chit et al. [21] for the US, estimating an ICER of US $145,705/QALY using a static model. From a societal perspective, cost-savings were reported by one static cost-comparison model in the US [27] and two dynamic models in the US and Germany [24,29] (Figure 3B). The highest ICER was in a scenario found by You et al. [34] for Hong Kong, estimating that in a season with a good match and an incremental vaccine price of US $10, the ICER could increase to US $254,245 per QALY gained [34] from the societal perspective.

Most studies drew a conclusion on whether implementing QIV could be regarded as a cost-effective intervention. However, most countries do not have an official willingness-to-pay (WTP) threshold, whereas the National Institute for Health and Clinical Excellence (NICE) in the UK considers a WTP threshold of US$29,070–43,600 (£20,000–30,000) per QALY for vaccines [45]. When no official thresholds were available, studies often referred to WTP thresholds used in earlier published cost-effectiveness studies or to recommendations of the World Health Organization (WHO), suggesting that an intervention is cost-effective if the ICER is below three times the gross domestic product per capita of a country [46]. Applying this WHO recommendation on the
### Table 4. Effectiveness and cost-effectiveness of QIV as compared with TIV and key parameters towards cost-effectiveness results.

<table>
<thead>
<tr>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Chit [20], Canada</td>
<td>1.25%</td>
<td>0.92%</td>
<td>78,303/QALY</td>
<td>52,169/QALY</td>
<td>QIV price, vaccine match, cross-protection of TIV, level of B circulation, hourly labor cost</td>
</tr>
<tr>
<td>Chit [21], United States</td>
<td>1.68%</td>
<td>0.72%</td>
<td>145,705/QALY</td>
<td>139,159/QALY</td>
<td>Not reported for QIV vs. TIV comparison</td>
</tr>
<tr>
<td>Clements [22], United States</td>
<td>0.15%</td>
<td>2.36%</td>
<td>NA</td>
<td>95,150/QALY</td>
<td>Cross-protection of TIV, vaccine match, level of influenza B circulation</td>
</tr>
<tr>
<td>de Boer [23], United States</td>
<td>29.2%</td>
<td>31.7%</td>
<td>31,934/QALY</td>
<td>27,891/QALY</td>
<td>Cross-protection of TIV, probabilities of death, vaccine efficacy</td>
</tr>
<tr>
<td>Dolk [24], Germany</td>
<td>4.02%</td>
<td>6.40%</td>
<td>18,760/QALY</td>
<td>CS</td>
<td>Probability of death, duration of natural immunity, disability of influenza</td>
</tr>
<tr>
<td>García [25], Spain</td>
<td>18,565 cases in one season</td>
<td>181 deaths in one season</td>
<td>16,695/QALY</td>
<td>13,054/QALY</td>
<td>Circulation influenza A, vaccine match</td>
</tr>
<tr>
<td>Jamotte [26], Australia</td>
<td>92 per 100,000 py (average)</td>
<td>0.92 per 100,000 py (average)</td>
<td>Total savings: 25.3 million</td>
<td>Total savings: 32.3 million</td>
<td>Influenza attack rate, cross-protection of TIV, proportion of influenza B, vaccine match</td>
</tr>
<tr>
<td>Lee [27], United States</td>
<td>1.40%b</td>
<td>1.40%b</td>
<td>Average annual costs: –30.5 to 344.7 million1</td>
<td>Average annual costs: –325.0 to 50.1 millionc</td>
<td>QIV price</td>
</tr>
<tr>
<td>Meier [28], United Kingdom</td>
<td>1.17%</td>
<td>3.59%</td>
<td>21,615/QALY</td>
<td>19,921/QALY</td>
<td>Circulation influenza A, vaccine match</td>
</tr>
<tr>
<td>Mullikin [29], United States</td>
<td>6.47%</td>
<td>7.00%</td>
<td>5,188/QALY</td>
<td>CS</td>
<td>Vaccine match</td>
</tr>
<tr>
<td>Nagy [30], Finland</td>
<td>11.3%</td>
<td>18.2%</td>
<td>CS</td>
<td>NA</td>
<td>Influenza transmission coefficient/infectious period and QIV price</td>
</tr>
<tr>
<td>Thommes [31], Canada and United Kingdom</td>
<td>Can: 4.62%</td>
<td>Can: 6.78%</td>
<td>Can: 6,551/QALY</td>
<td>NA</td>
<td>QIV price, outcome probabilities, and inclusion of illness-related QALY loss</td>
</tr>
<tr>
<td>van Bellinghen [33], United Kingdom</td>
<td>0.69%</td>
<td>2.82%</td>
<td>8,611/QALY</td>
<td>NA</td>
<td>distribution influenza A and B, vaccine match, QIV price</td>
</tr>
<tr>
<td>You [34], Hong Kong</td>
<td>65–79 y: 118 per 100,000 py. ≥80 y: 508 per 100,000 py (only influenza B)</td>
<td>65–79 y: 0.0589 per 100,000. ≥80 y: 0.254 per 100,000 py (only influenza B)</td>
<td>NA</td>
<td>65–79 y: 14,906–254,245/QALY, ≥80 y: CS–70,147/QALY</td>
<td>QIV price</td>
</tr>
<tr>
<td>You [35], Hong Kong</td>
<td>14.7%</td>
<td>14.9%</td>
<td>23,335/QALY</td>
<td>12,965/QALY</td>
<td>QIV price and proportion influenza B</td>
</tr>
</tbody>
</table>

Can: Canada; CS: cost saving; NA: not applicable; py: person years; QALY: quality-adjusted life-years; QIV: quadrivalent influenza vaccine; TIV: trivalent influenza vaccine; UK: United Kingdom. aBased on judgment of the reviewers. bFor Lee et al. [27], reductions in influenza cases and deaths were directly adapted from Reed et al. [42]. cShown for a QIV versus TIV price difference ranging from US $0 to US $5; Results were derived from the published corrigendum [36]. dUK1: Vaccine uptake rate of 52.5% in children aged 2–17 years. UK2: Vaccine uptake rate of 70% in children aged 2–17 years. eEU5 includes France, Germany, Italy, Spain, and United Kingdom. EU27 results were based on extrapolations of EUS. fShown for a QIV versus TIV price difference ranging from US $1 to US $10. The season 2002 was excluded as no results were presented for this year.
US would result in a WTP threshold of US $150,000 per QALY gained. All cost-utility studies concluded that vaccination with QIV would be at least cost-effective as compared with TIV, when official or hypothetic thresholds were considered [20–25,28–31,33–35].

3.6. Key drivers of cost-effectiveness results

Parameters that were found to be of highest impact on cost-effectiveness outcomes are shown in Table 4. The four most reported key parameters were vaccine price of QIV, the level of cross-protection of TIV against the mismatched B virus strain, the distribution of influenza incidence between influenza A and influenza B, and the level of vaccine match of TIV with the circulating B lineages (Table 4). Obviously, higher vaccine price differences between QIV and TIV resulted in less beneficial cost-effectiveness outcomes. For instance, Nagy et al. [30] found that when an incremental vaccine price of US $3.96 for QIV over TIV would be assumed instead of price parity, the estimated amount of cost saving would be reduced by 30%. Also, the high ICER of US $139,027 per QALY gained for the US elderly by Chit et al. [21] could be explained by a relatively high vaccine price of QIV.

The impact of cross-protection of TIV to the opposite B virus strain on the cost-effectiveness was explicitly illustrated by the study of de Boer et al. [23], showing that decreasing the level of cross-protection from 70% to 50% in the US turned the ICER from US $27,891 per QALY gained into cost-saving/dominant. Furthermore, the circulation and distribution of, respectively, influenza A and influenza B and related vaccine matching/efficacy had also a strong effect on the ICER. For example, van Bellinghen et al. [33] noted that, in a scenario of 0.4% circulation of influenza B, the ICER would rise to US $450,000 per QALY gained. Additionally, in a scenario of 99.0% matching of TIV with the circulating influenza B virus strain instead of 52.3%, the ICER would rise to US $450,000 per QALY gained.
4. Expert commentary

This is the first systematic review concerning the health-economic value of QIV so far. According to the current literature, QIV appears to be a cost-effective intervention as compared with TIV. All studies found that QIV resulted in valuable health benefits as compared with TIV by reducing influenza-related morbidity and mortality within a range of 0.15–6.5%. Additionally, QIV was estimated to save costs to the healthcare system and to society, partially or even fully compensating for the higher vaccine price of QIV compared to that of TIV. Although conclusions on cost-effectiveness were generally similar, we found substantial heterogeneity across cost-effectiveness results. ICERs varied from cost-saving to $146,000 from a health-care payer’s perspective and cost-saving to $140,000 from a societal perspective. Identified key parameters to cost-effectiveness outcomes included vaccine price, circulation of the B-virus not included in TIV and cross-protection of TIV against the opposite B-virus.

Modeling approach was found to be important with regard to cost-effectiveness results. Despite the recommendations of Quinn et al. [13] and working groups on cost-effectiveness analyses of vaccines [40,47], only five studies used a dynamic transmission model. We found that dynamic models predicted a higher impact of QIV on influenza morbidity than static models, resulting in better cost-effectiveness outcomes. Vaccination reduces the overall influenza transmission within a population. As static models use a constant force of infection, they do not quantify the indirect impact of vaccination. Therefore, we recommend that, although static models can be informative for an initial preliminary analysis, dynamic models are required to study the full impact of QIV on health-economic outcomes. Obviously, the downside of this recommendation is that dynamic models demand more (fine-grained) input data than static models [41].

Notably, the impact of modeling approaches depends on the current vaccination policy of the studied country. Countries with universal influenza vaccination recommendations, such as the US, have relatively high vaccination coverage among children. As children seem to represent an important group in influenza transmission [48,49], the additional impact of dynamic models over static models will be higher in countries with universal vaccination as compared with countries restricting influenza vaccination to elderly and specific high-risk groups. Additionally, when – from a societal perspective – cost savings due to (parental) work loss are taken into account, potentially better cost-effectiveness outcomes may ensue. On the other hand, complication rates are highest among the elderly. Therefore, we would emphasize that cost-effectiveness outcomes might be highly influenced by the target group of the vaccination program.

An important key aspect to cost-effectiveness outcomes is whether cross-protection of TIV against the mismatched B virus is taken into account. As mentioned by Quinn et al. [13], recent evidence suggests that cross-protection of TIV to the opposite influenza B virus exists, potentially diminishing the impact of QIV significantly [43,44]. Our review shows that the majority of studies included cross-protection in their analyses. Most studies referred to systematic reviews by Tricco et al. [43] and DiazGranados et al. [44], estimating that the vaccine efficacy of TIV against the non-included B virus strain is 65–70% of the matched efficacy. Studies on single influenza seasons confirmed the finding of cross-protection during the 2012–2013 season in the US and Canada [50,51], but not during the 2011–2012 season in Canada [50]. Additionally, a recently published serological study demonstrated that antibodies elicited with inactivated TIV containing a Victoria-lineage strain were highly cross-reactive to a Yamagata-lineage strain [52]. As current evidence supports the existence of cross-protection, we endorse the inclusion of this aspect in cost-effectiveness models. However, as bias cannot be ruled out due to pre-existing immunity as a result of prior vaccination or natural infection, the exact estimate is unclear. Therefore, we highly recommend to perform sensitivity analyses on this parameter.

Another key parameter influencing cost-effectiveness outcomes is the vaccine price. Many studies had to make assumptions on the price premium of QIV as compared with TIV, since no official vaccine price was available at the moment of analysis. Therefore, the vaccine price should be taken into account when interpreting results, as for instance cost-effectiveness studies assuming a price parity between QIV and TIV will almost automatically result in cost-saving outcomes. On the other hand, assuming price parity in the absence of an official QIV price and just showing the expected net health benefit of QIV over TIV avoids drawing the wrong conclusion. Cost-effectiveness results could then be easily updated when a vaccine price becomes available. Currently, price lists of the US CDC show that the vaccine manufacturers increased the price of inactivated QIVs significantly, at around 50% higher than inactivated TIVs, although there was no price increase shown for Q-LAIV as compared with trivalent LAIV [53]. However, in large-scale public health programs, such as influenza vaccination, vaccines might be procured at relatively lower prices than indicated by the list prices.

Cost-effectiveness results also tend to be highly sensitive to the level of circulation of the influenza B virus. In seasons with a proper vaccine match and no co-circulation of both B lineages, the effect of QIV over TIV is likely to be negligible. This was highlighted in some studies that analyzed the impact of QIV retrospectively over the period 2001–2010, demonstrating a wide variation in cost-effectiveness results between different seasons [27,33,34]. As any influenza virus, influenza B incidence varies across countries and regions [45]. For instance, three studies estimated the proportion of mismatched influenza B infections at 50% of the total influenza B infections in the US between 1999 and 2009, in line with 52.6% in Australia between 2002 and 2012, and 52.4%, in the UK between 2000 and 2010 [22,26,33]. However, the study by Heikkinen et al. [54] found that this proportion was only 41.7% in Finland in the period 1999–2012. Therefore, studies analyzing the retrospective impact of QIV should aim to use country-specific data.

We noticed that most studies used equal estimates of resource use and costs across all influenza subtypes. As suggested by Quinn et al. [13], influenza B might be associated with higher morbidity in children as compared with the elderly. In the elderly, highest hospitalization and mortality
rates were found for the influenza A/H3N2 subtype, followed by influenza B virus and the A/H1N1 subtype. Usage of outcome estimates that are not specified by seasonal influenza subtype might therefore be considered nonoptimal. However, a study of Mosnier et al. [55] showed that despite differences in age-distribution between influenza A and influenza B, no differences on clinical severity were found between influenza virus types and subtypes among GP visiting influenza cases. Notably, when influenza B causes less severe disease in adults and the elderly as compared with influenza A, patients with influenza B will be underrepresented at medical facilities to undergo laboratory testing for subtype. This may complicate the split of influenza cases by subtype as performed in static models. A further complication might be that available data on laboratory tests were often subtyped between A and B, but not between B/Vic and B/Yam [56]. Regarding influenza-related mortality, the impact of QIV might be overestimated when A/H3N2 is indeed related to higher mortality in elderly than influenza B. As data on influenza B incidence and its resource use are still not widely available, more evidence on incidence and resource use by subtype would be desirable to improve the validity of cost-effectiveness results.

Next to nonlinear influenza epidemiology by age and subtype, pre-existing immunity due to prior natural influenza infection or vaccination history might induce inaccuracy. Duration of naturally acquired immunity is expected to be influenced by the natural waning of immunity within the individual as well as the drift of influenza viruses over time [57]. However, evidence on this aspect is, to the best of our knowledge, still scarce. Dynamic modeling studies included in this review, predominantly derived inputs for this parameter from a study of Vynnycky et al. [58]. This study calibrated a dynamic model on influenza incidence patterns of the UK, with optimal fit occurring when durations of naturally acquired immunity were set at 6 years for influenza A and 12 years for influenza B. Also a study by Eichner et al. [39], describing the influenza dynamics for Germany, assumed a longer naturally acquired immunity for influenza B as compared with influenza A/H3N2 (3.5 years versus 7 years). The study of Nagy et al. [30] found eligible simulations during this parameter from a study of Vynnycky et al. [58]. This study calibrated a dynamic model on influenza incidence patterns of the UK, with optimal fit occurring when durations of naturally acquired immunity were set at 6 years for influenza A and 12 years for influenza B. Also a study by Eichner et al. [39], describing the influenza dynamics for Germany, assumed a longer naturally acquired immunity for influenza B as compared with influenza A/H3N2 (3.5 years versus 7 years). The study of Nagy et al. [30] found eligible simulations during their calibration process for durations of naturally acquired immunity against influenza B ranging between 0.5 and 75 years. A recent dynamic modeling study from Japan [59], however, estimated much shorter durations of natural immunity against influenza B than the above mentioned studies, estimating 1.15 years for B/Vic and only 0.08 years for B/Yam, although this does not align well with current knowledge on the relatively conserved antigenic nature of influenza B [60]. For the duration of vaccine-induced protection, a recent study by Kissling et al. [57] suggested that protection against influenza B was longer than that against influenza A/H3N2, possibly due to a more rapid antigenic drift of A/H3N2 [61]. Related to this aspect, Höpping et al. [62] recently presented an approach to optimize the effectiveness of TIV by choosing the included influenza B strain on the basis of the population’s pre-existing immunity instead of taking the virus strain that circulated in the prior season. They argued that by taking into account the time since vaccination, antigenic drift, and serological parameters of each B virus strain, the level of residual protection against B/Yam and B/Vic could be estimated. By selecting the influenza B virus strain with the lowest residual protection, high protection levels against both influenza B viruses would be present after vaccination, potentially giving a better protection in case of a vaccine mismatch. Although this strategy is expected to be still inferior to QIV, Höpping et al. [62] suggested that it might at least partially capture the benefit of QIV, without any additional vaccine costs. So far, no study has ever compared the cost-effectiveness of QIV versus TIV using this ‘Höpping’ approach, which, however, might be of interest and complement existing studies.

With regard to the quality of reporting according to the CHEERS criteria [15], we found that adherence to this checklist was acceptable. However, we noticed that only a few studies provided arguments whether the chosen time horizon was appropriate to capture all the various effects and consequences of the intervention. Indeed, influenza is often considered a seasonal issue, with each year different types and/or subtypes of influenza predominantly circulating, varying in disease severity. Yet, considering the fact that influenza is an annual recurrent disease with potential crossover effects from season to season, a time horizon of more than one year is needed to capture all the various effects and consequences of vaccination policies. Hence, models should transparently argue whether their chosen time horizon is long enough to include relevant subsequent effects.

A second concern that emerged from the analysis using the CHEERS checklist relates to the exact descriptions of the population and instruments used to estimate the impact of influenza on quality-of-life. We noticed that many of the included studies used utilities from outdated studies (mostly other models) that were based on small sample sizes. Updating a systematic review on studies measuring the impact of quality-of-life estimated of influenza morbidity by Van Hoek et al. [63], we found that the evidence on this aspect is still limited [64]. Although two studies were published that used EQ-5D to measure quality-of-life of influenza morbidity based on larger sample sizes [63,65], generalizability might be limited as these analyses were conducted among patients infected with the pandemic H1N1 influenza strain. As pandemic H1N1 was generally seen as a milder variant of disease than A/H3N2 in adults, these values might not be truly representative for seasonal influenza in general [66]. Therefore, we recommend precise studies on estimating the quality-of-life in laboratory-confirmed seasonal influenza patients with standardized instruments.

The reporting regarding performed validation processes was found to be limited. A proper validation process of the model and its transparent reporting will improve the credibility of the model outcomes. Although most studies performed cross-validation of model outcomes to similar studies, these comparisons are mostly hampered by differences between model types and/or model inputs. Notably, as the inclusion of parameters such as waning of immunity or antigenic drift of viruses strongly enhance the complexity of (dynamic) models, validation techniques on the computerized model and its outcomes will become increasingly important. Obviously, the transparency of a model increases considerably by making the model publicly available, which – to the best of our
knowledge – was only done for the model used in the Canadian study by Chit et al. [20]. In addition, we would advocate the use of structured model validation checklists, as researchers tend to do more validation efforts than they report in their manuscripts [67].

Finally, we found that the majority of the studies were funded by pharmaceutical companies. We feel that, in addition to these sponsored studies, also publicly funded economic evaluations of QIV are needed to validate the findings from industry-funded studies. Furthermore, there were no studies performed in low- and middle-income countries (LMICs), where it would also be valuable to know if more restricted budgets could be better spent on QIVs or TIVs. Indeed, due to differences in demographics, comorbidities, and healthcare facilities, results from industrialized countries are not directly transferable to LMICs. For instance, as influenza B rather tends to infect adolescents and young adults than elderly, the impact might be higher in LMICs which generally have younger populations. An individual-based modeling exercise found that QIV would reduce influenza-related hospitalizations and deaths by 18% as compared with TIV in a community in South Africa between 2003 and 2013, while this was only 2% in Australia in the same period [68].

The main limitation of our study is that our search was restricted to the English language. A major strength of our study is that we systematically searched for economic evaluations of QIV using multiple databases. We converted study results to the same price year and corrected for differences in purchasing power to enhance comparability. Another strength is that we checked whether the key challenges mentioned by Quinn et al. [13] were addressed properly. We also included studies in which the primary goal was not to evaluate the cost-effectiveness of QIV as compared with regular TIV, but for instance with high-dose TIV or adjuvant TIV [21,29], with cost-effectiveness of QIV emerging as an additional result. Chit et al. [21] estimated that a high-dose TIV, containing four times higher viral-loads as compared with regular TIV, would be more effective in preventing influenza disease in US elderly as compared with QIV. From the societal perspective, the authors estimated that high-dose TIV would be cost-saving as compared with QIV or US $5,157 per QALY gained as compared with regular TIV. Mullkin et al. [29] found from a societal perspective that TIV adjuvanted with the squalene-containing oil-in-water emulsion MF59 would be cost-saving in US elderly as compared with regular TIV and QIV.

In conclusion, published evidence of the economic consequences found that quadrivalent influenza vaccination is expected to be a cost-effective intervention as compared with TIV. However, the cost-effectiveness potential is strongly related to the price difference between QIV and TIV, and the level of cross-protection that TIV provides against the B virus strain that is not included in the vaccine. In other words, the benefits of QIV will vary strongly by season according to the match of TIV with the circulating B virus strain. It is therefore recommended to assess the impact of QIV versus TIV using data from multiple influenza seasons, which on average will give a better reflection of influenza B virus strain circulation from one year to another. As previously discussed by Quinn et al. [13], we support the inclusion of cross-protection of TIV against the mismatched B virus, the use of influenza B-specific data to estimate the disease burden, and the use of dynamic models. As we noticed that influenza B-specific data on disease burden and costs remains scarce, we recommend more research into these topics.

5. Five-year view

With regard to the future, we endorse studies aiming to unravel the immunogenicity of natural influenza infection and vaccination. Uncertainty around potential influential aspects like cross-protection, duration of vaccine-induced and natural immunity is large. Further insight into these aspects will improve the understanding and modeling of influenza transmission dynamics. However, as modeling of the relationship between (drifting) influenza viruses and immunity in the human population will increase the complexity of dynamic modeling, we would also advocate proper and transparent model validation processes in order to guarantee continued adequate evidence-based immunization decision-making.

Although newly developed influenza vaccines, like high-dose vaccines and adjuvanted vaccines, have been shown to have improved immunogenicity and may, potentially, induce better cross-protection as compared with standard vaccines [69,70], their efficacy toward unmatched viruses remain to be analyzed. To definitively overcome this issue, the development of broad-spectrum influenza vaccines is currently widely explored [71]. These so-called ‘universal’ vaccines aim to induce a humoral response against viral antigens or antigenic epitopes which are not affected by antigenic drift or they may activate a different immune pathway like the cellular immune response [60]. Universal vaccines may thus provide protection against not only many different viral strains and drift variants, but also against antigenically shifted viruses with pandemic potential. A recent modeling exercise demonstrated that such broad-spectrum vaccines have the potential to interrupt influenza transmission even at moderate uptake levels [72]. Although some promising broad-spectrum vaccines have entered already the phase of testing in clinical trials [60], it remains uncertain whether and when such vaccines will become publicly available. Certainly, duration of vaccine-induced protection will become a very important aspect with regard to the public-health impact and cost-effectiveness of these vaccines.

Key issues

● Quadrivalent influenza vaccines (QIVs) contain one additional influenza B strain as compared with trivalent influenza vaccines (TIVs).
● Quadrivalent influenza vaccination is supposed to provide better protection in seasons with a mismatch between TIV and the circulating B virus lineage or in seasons with cocirculation of both influenza A and B lineage.
In this review, we identified 13 cost-effectiveness studies and three cost-comparisons of QIV versus TIV.

Studies predominantly estimated QIV to be a cost-effective or even cost-saving intervention from payer’s and societal perspectives.

Levels of mismatched influenza B circulation, cross-protection of TIV to the mismatched B virus and the QIV price premium were identified as key factors influencing health-economic outcomes.

Enhanced use of dynamic transmission models is recommended as these models account for indirect effects of vaccination on unvaccinated individuals.

As disease burden might differ by influenza subtype, cost-effectiveness studies should be improved with subtype-specific data and increased evidence on this aspect should be made available.

Better understanding of influenza immunogenicity by natural infection and vaccination is needed to improve simulations of influenza dynamics.

Given the increasing complexity of (dynamic) influenza models, systematic validation of the model and its outcomes is strongly recommended.

**Funding**

This paper was not funded.

**Declaration of interest**

The appointments of PT de Boer and FCK Dolk are partly supported by grants of different pharmaceutical companies, including companies involved in the subject matter of this study. BM van Maanen and B Ultsch report no conflicts of interest. O Damm conducted studies for pharmaceutical companies, including companies involved in the subject matter of this study. P Crépey, RP Pitman, JC Wilschut and MJ Postma have received grants and honoraria from pharmaceutical companies, including companies involved in the subject matter of this study. The authors have no other relevant affiliations or financial involvement with any organizations or entities with a financial interest in or financial conflict with the subject matter or materials discussed in the manuscript apart from those disclosed.

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Papers of special note have been highlighted as either of interest (∗) or of considerable interest (∗∗) to readers.


**Explains key issues on estimating the cost-effectiveness of the quadrivalent influenza vaccine**


**Cost-effectiveness study of QIV versus TIV using a dynamic transmission model**

• Cost-effectiveness study of QIV versus TIV using a dynamic transmission model.


• Cost-effectiveness study of QIV versus TIV using a dynamic transmission model.


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