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A Framework for Analyzing Transformative Technologies in Life Cycle Assessment

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Emerging products and technologies pose unique challenges for the life cycle assessment (LCA) community, given the lack of data and inherent uncertainties regarding their development. An emerging technology that has the potential to be transformative and effect broad-scale change within society, as well as the underpinning assumptions associated with its life cycle, is particularly difficult to analyze. Despite the associated challenges, LCA methods must be developed for transformative technologies. The greatest improvement potential occurs at the early phases of technology development; therefore, prospective LCA results can be used to anticipate potential unintended consequences and develop design pathways that lead to preferential outcomes. This paper identifies and categorizes ten factors that influence the LCA results of transformative technologies in order to provide a formal structure for determining appropriate factors for inclusion within an LCA. Appropriate factors for an analysis should be selected according to the overall research questions of the study and are applicable to both attributional and consequential approaches to LCA.

Introduction

A transformative technology is a product or process that has the potential to fundamentally change existing markets, develop new markets, lead to changes in consumer behavior, or significantly alter major supply chains. Transformative technologies, sometimes termed disruptive innovations, include both new products and existing products with improved functionality. There are many products and processes that fall within this category, such as nanotechnology, alternative energy sources, and various advances to communication, mobility, and information systems. By definition, a transformative technology changes the system or systems with which it is associated. The adoption of a transformative technology will therefore alter some of the embedded assumptions within its own life cycle inventory (LCI). Often termed prospective LCA, a variety of studies have tackled aspects associated with emerging technologies, undertaking modeling efforts to better understand potential trends and overall effects of product adoption [1-6]. The majority of existing literature on transformative technologies has focused on generating bounded range estimates for technology improvements and market penetration. There

has also been significant discussion regarding the types of uncertainty associated with such analyses [3, 7, 8] and guidance for constructing potential future scenarios [3, 9-11].

The evolving nature of a transformative technology has implications for both attributional and consequential LCA [12]. Whereas attributional LCA focuses on the measurable flows of energy and materials directly associated with a product and its supply chain, consequential LCA measures the overall change of the system associated with the product. These LCA approaches have different conventions and purposes that have been extensively discussed and reviewed elsewhere [13, 14]. Rather than comparing the methodological details of different LCA approaches, this paper seeks to fill a gap in the literature by providing a comprehensive overview and systematic framework to identify key factors that influence LCA results of transformative technologies. While all transformative technologies are emerging, not all emerging technologies have the potential to be transformative. It is expected that the proposed structure is applicable to all new technologies, although the factors pertaining to societal-scale transitions may have negligible impacts on the LCA results of non-transformative emerging technologies.

This paper identifies ten factors commonly associated with transformative technologies and discusses their suitability to address different research questions, highlighting methods that have been established to incorporate these factors into the LCA protocol. As with any LCA, the factors to be included within a particular study should be chosen in accordance with the research questions guiding the analysis. Given the number of potentially relevant research questions surrounding a transformative technology, it may not be logistically possible to address all factors within a single LCA. An integrative, interdisciplinary approach to transformative technology assessment can provide a robust examination of the system's overall complexity and lead to better identification of potential improvements. To accomplish such a comprehensive analysis, several complementary studies using a variety of disciplinary perspectives may be more appropriate and realistic than any single approach.

To illustrate how each of the identified factors can affect an LCA, plug-in hybrid electric vehicles (PHEVs) and online commerce are used as case studies. These examples are chosen due to their transformative potential, the relevance of each factor, and data availability. The case studies also represent dissimilar sectors to show the broad applicability of the identified factors.

Methods

This section identifies ten factors relevant to the comprehensive study of transformative technologies. Each factor is categorized as intrinsic, indirect, or external. *Intrinsic factors* are directly associated with the product or technology and affect fundamental assumptions embedded within its LCI. *Indirect factors* change the LCI as a result of the technology's interactions with the existing system. Finally, *external factors* affect the LCI of the technology, but occur independently of technology deployment. Figure 1 depicts the system of categorization and the interactions of a transformative technology with the existing system.

Most LCAs assume steady state, resulting in a snapshot of a particular system condition. Transformative technologies evolve, resulting in shifting inventory data that require incorporation of

temporal considerations into the analysis. Dynamic LCA principles provide guidance to conduct analyses under non-equilibrium conditions [15, 16]. The selected timeframe of scenario predictions can have a dramatic effect on LCA results. Forecasts 10 years into the future are characterized by a lower level of uncertainty than forecasts of 50 years or more. The temporal aspects of an analysis influence each of the ten factors considered within this paper. Since temporal effects cannot be considered independent factors that can be selected for inclusion or exclusion within a transformative technology LCA, they are not included in the proposed framework. Nevertheless, different temporal considerations will have obvious impacts on the LCA of transformative technology and explicit treatment of temporal factors is an inherent and necessary element of any transformative technology assessment.

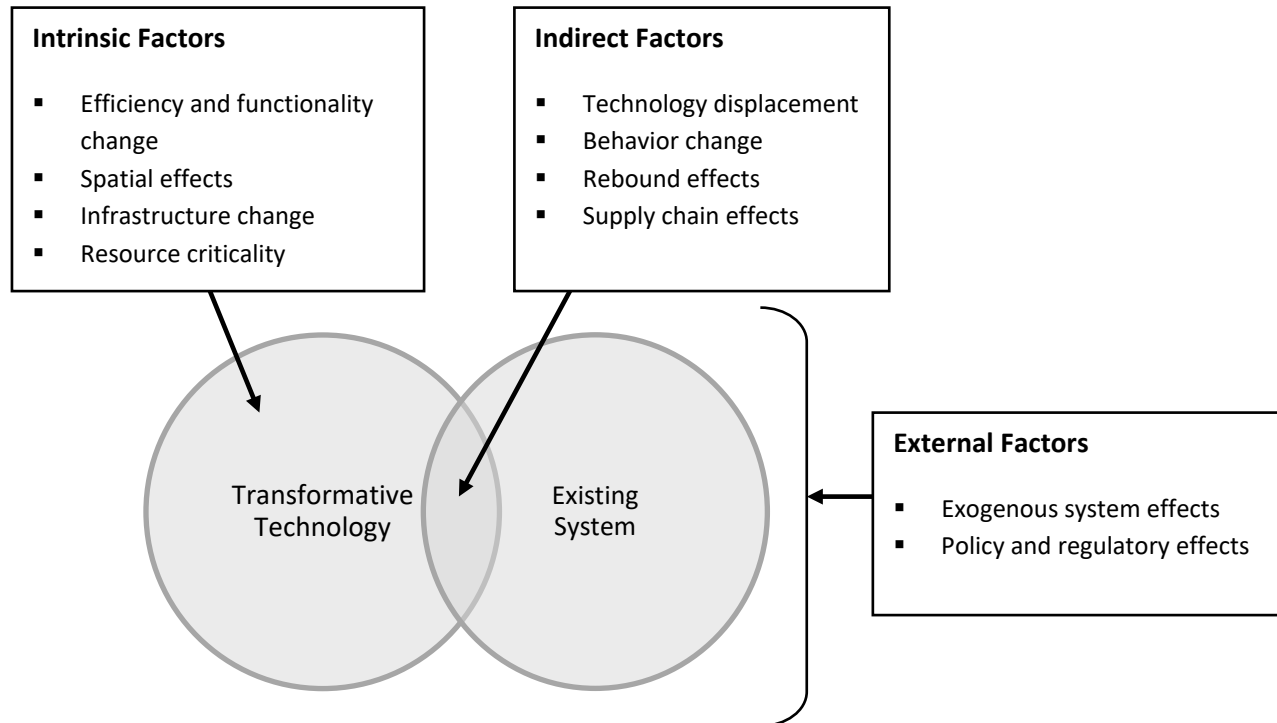


Figure 1. Schematic characterizing ten factors that impact the LCA results of a transformative technology. Intrinsic factors are directly associated with the technology's life cycle. Indirect factors occur at the interface of the technology and the existing system and characterize the impacts resulting from interactions with the existing system. External factors occur irrespective of the technology's adoption, yet influence its LCA results.

Intrinsic Factors

Intrinsic factors have a direct impact on the embedded assumptions of an analysis. Although implicitly included in every LCA, the assumptions surrounding these factors tend to be both dynamic and uncertain. Intrinsic factors are commonly discussed when creating future scenarios for an LCA due to their major influence on results. The intrinsic category includes four factors: efficiency and functionality change, spatial effects, infrastructure change, and resource criticality. Factors in this category are applicable to both attributional and consequential LCA.

Efficiency and functionality change

Products evolve over time, generally exhibiting improved performance and greater efficiency. Improved efficiency is frequently modeled in prospective LCA since product performance is directly related to the underpinning assumptions of functional unit calculation [17, 18]. As products mature, they often develop additional functionality in addition to efficiency improvements [19, 20]. The manufacturing process for a new product is often less efficient than for an existing product, yet the rate of improvement for the new technology is expected to outpace the rate of improvement of the established technology. A study by Gavankar et al. describes how manufacturing readiness level should be taken into account when compiling an LCI for emerging technologies [21]. In addition, anticipated efficiency improvements and changes to expected service lifetime may affect product replacement recommendations and overall LCA results [22].

Spatial Effects

Spatial considerations that affect LCA results include differential regional inventory emissions (i.e. the electricity grid), differential adoption patterns (i.e. technology deployment in rural versus urban areas), and differential impacts according to the susceptibility of a region to environmental damage (i.e. acid buffering capacity of water bodies) [23]. The LCA community has identified the need to create and expand spatially explicit LCI [24]. Geographically explicit inventory emissions can have a significant effect on LCA results when compared to aspatial data [25]. For non-dispatchable renewable energy technology such as wind and solar, the location of deployment impacts the performance efficiency and integration into the existing grid [26]. Adopters located in different countries or in urban versus rural areas may interact with a technology differently, which will affect inventory assumptions. For example, the extent of urban sprawl and other factors contributing to urban form will influence overall miles traveled, as well as lifetime fuel economy of vehicles [27].

Infrastructure Changes

Transformative technologies generally require some level of accompanying infrastructure change. When amortized to a functional unit basis, the environmental burden of infrastructure construction tends to be small [28]. Within the LCA protocol, infrastructure is considered a tertiary consideration and generally falls outside the boundary definition of most established products; however, a recent study on transportation systems suggests the life cycle effects of transportation infrastructure are not insignificant and automatically excluding infrastructure considerations from life cycle boundaries may not be appropriate [29]. Inclusion of infrastructure into the boundaries of an LCA for transformative technologies may significantly impact the results, at least in the near term. When conducting comparative LCA, it is important to use consistent boundaries, which includes treatment of infrastructure considerations. For example, it is common to include construction impacts of renewable energy technologies but neglect analogous infrastructure associated with fossil fuel technologies [30], resulting in inconsistent boundaries.

Resource Criticality

Resource criticality, or scarcity, is an important issue when assessing the sustainability of global supply chains [31]. Resource criticality may be of particular importance to include in the impact assessment

phase within an LCA if a technology's introduction induces new or significant additional stress on a resource. If the transformative technology consumes resources that are sufficiently scarce and the technology has ample market penetration, resource criticality may be an important factor to assess. For example, implementation of a water-intensive technology may place substantial stress on water resources in arid regions [32]. Supply chain shortages can result from physical as well as geopolitical scarcity [33]. Resource criticality is often not addressed directly in impact assessment methods beyond quantification of resources consumed, although recent studies have suggested methods to account for depletion and stress to measure criticality [34, 35].

It is reasonable to argue that resource criticality belongs in the indirect factor category because criticality is a function of interactions within the larger system; however, it is included in the intrinsic category because the quantity of material consumed is inherent to the product's design.

Indirect Factors

Indirect factors affect the LCA as a result of the technology's interaction with the existing system. Four factors are identified as indirect: technology displacement, behavior change, rebound effects, and supply chain effects. Indirect factors are typically associated with consequential approaches to LCA, although some indirect factors such as behavior change have been included in attributional studies.

Technology Displacement

The net environmental impact of a new technology depends on the baseline environmental impacts of the technology (or technologies) it displaces. Technology displacement measures the marginal change in environmental impact due to an emerging technology, rather than the absolute environmental impacts throughout its life cycle [36]. In order to determine the net system change for a consequential LCA, it is necessary to determine whether a new product displaces existing technology or is an additive technology. LCA methods must be coupled with some other modeling technique in order to estimate this type of information.

Often, economic models are employed to determine the extent of displacement effects. For example, economic equilibrium models have been used to quantify indirect land use change caused by increased bioenergy production and the subsequent displacement of food crops. Significant disparities exist regarding modeling assumptions, approaches, and the results of indirect land use change emissions estimates [37]. Nevertheless, indirect effects are consequences of system disruption and are of particular importance for transformative technology. LCA researchers have suggested alternative methods to model potential technology displacement that do not require equilibrium models, although economic considerations are usually included in some manner. Example approaches include construction of experience curve models to estimate future reduction in production costs [38] and game theory to show the incentives needed for new technology to compete with the status quo [39].

Modeling technology displacement is particularly challenging for complex, multi-functional products (i.e. computers, smart phones, buildings, cities, food), where LCA results are highly dependent on functional unit choices [40]. The functional unit of a complex product is often limited to a single function (i.e.

169 10,000 pages of data, 200 kcals) rather than incorporating its entire spectrum of functions. For example,
170 tablet computers overlap functionality with multiple gadgets, including laptops, media players, and
171 cameras, but it is unclear whether these multifunctional devices displace products with similar functions
172 or supplement their existence [41].

173

174 *Behavior Change*

175 Transformative technologies initiate sociological change as well as technological disruption. A
176 sufficiently disruptive technology can change societal norms [42]. For example, affordable personal
177 vehicles (and the subsequent construction of highway systems) changed personal freedom, access to
178 employment, and the overall design of cities. In this framework, behavior change includes only the
179 changes in behavior that directly result from interacting with the technology itself. Changes in
180 consumption patterns induced by improved system efficiency are categorized as rebound effects,
181 whereas changes in societal behavior patterns that are independent of the technology are classified as
182 exogenous system effects.

183 Although highly variable and uncertain, behavior patterns can have a dramatic effect on the embedded
184 assumptions within an LCA [43]. Consumer behavior is most likely to be affected when consumers have
185 direct interaction with the product, as opposed to changes in less visible technologies, such as
186 improvements to the electricity grid. Building performance, for example, is highly dependent on
187 occupant behavior [44]. Although the results of studies on the relationship between energy efficient
188 buildings and behavior change are mixed [15], it is well known that new technologies can directly
189 influence behavior and corresponding environmental performance of a given technology.

190 *Rebound Effects*

191 The rebound effect is characterized by increased consumption resulting from improved efficiency [45].
192 Rebound effects can be observed through both consumer behavior and technological design. A rebound
193 effect associated with consumer behavior results in increased consumption due to cost savings, such as
194 increased miles driven as a result of improved fuel economy. A frequently assessed phenomenon,
195 rebound effects are included as an independent factor to be considered within LCA since they are
196 induced behavior effects rather than a direct behavior change resulting from interacting with the
197 technology. Rebound effects related to technological design pertain to increased functionality due to
198 improved efficiency. Using the internal combustion engine as an example, improved engine efficiency
199 does not always result in better fuel economy. Instead, greater demands may be placed on the engine
200 as more features are added to enhance passenger comfort which can increase accessory load and/or
201 vehicle mass [46].

202 The presence of the rebound effect may confound LCA results. In a recent study, Deng and Williams
203 found that semi-conductors became less energy intensive over time when analyzed on a functional unit
204 basis; however the microchips exploited these gains to achieve greater functionality and increased
205 computational power [20]. Although calculation of impacts on a functional unit basis is one of the
206 foundational principles of LCA, the authors suggest that conducting assessments on a per-product basis
207 and taking into account functional evolution over time may be a more accurate measure of
208 environmental impact of transformative technologies [20].

209 *Supply Chain Effects*

Any fundamental shift in the supply chain can change baseline life cycle inventory values. Transformative technologies may cause shifts in upstream or downstream production to meet changes in supply or demand. For example, a major increase in demand for a specific petroleum product can alter oil refinery operation to produce an alternate product mix [47]. Introduction of horizontal drilling coupled with hydraulic fracturing has facilitated production of shale gas, which has far-reaching implications for the environmental impact of the electricity sector [48]. Meanwhile, other technologies may precipitate downstream changes such as development of new recycling technologies or waste treatment infrastructure.

External Factors

Whereas intrinsic and indirect factors are related to assumptions regarding the technology's deployment, external factors are independent of the technology, yet affect LCA results. The framework contains two external factors: exogenous system effects and policy and regulatory effects. Inclusion of external factors may be appropriate for either attributional or consequential LCA.

Exogenous System Effects

Exogenous system changes occur irrespective of the product's adoption. As society evolves over time, inevitable changes to life cycle inventory data will occur. Increased population and wealth will induce increased consumption pressure, contributing to shifting market dynamics and supply chains. Electricity grids will become more efficient, consumer needs and behavior patterns will change, and any number of other societal factors will be different in the future. Some of the changes will be predictable and some, due to disruptive technologies, are more difficult to forecast. Scenario modeling efforts can be helpful to understand potential changes to the technosphere that are independent of a product's evolution [15]. These changes may have dramatic effects on the LCI of any technology, and can affect different sectors disproportionately.

Policy and Regulatory Effects

A specific and important subset of exogenous system changes, policy and regulatory changes are included as an independent factor since they are often addressed explicitly by LCA practitioners. The policy and regulatory environment can have major impacts on a technology and its system. To illustrate this factor, a case study comparing the effect of different environmental regulation scenarios on transportation showed that different policy options can affect the relative emissions inventories of different modes of transportation [3]. Policies do not need to be directed specifically at the new technology to have an effect on its LCI. For example, changing regulations to the electricity sector have far reaching implications for the emissions inventory of many different sectors. Although policies and regulations may have very direct impacts on the product's LCI, these effects are included in the external factor category since they are independent pressures that initiate a system change and are a consequence of the greater socio-political context.

246 **Case Studies**

247 This section presents a brief review of two case studies to show how each of the ten identified factors
248 can affect LCA results. Figures 2 and 3 demonstrate how each factor interacts with the LCA of plug-in
249 hybrid electric vehicles (PHEVs) and online commerce, respectively.

250 The typical functional unit for a PHEV is passenger-miles, whereas the functional unit for online
251 commerce is less straightforward. Generally, the function of online commerce is confined to a specific
252 product purchase in order to limit the analysis to a concrete and reasonable scope. Regardless of the
253 functional unit chosen for a particular study of online commerce, the ten identified factors should have
254 same general impact on the LCA.

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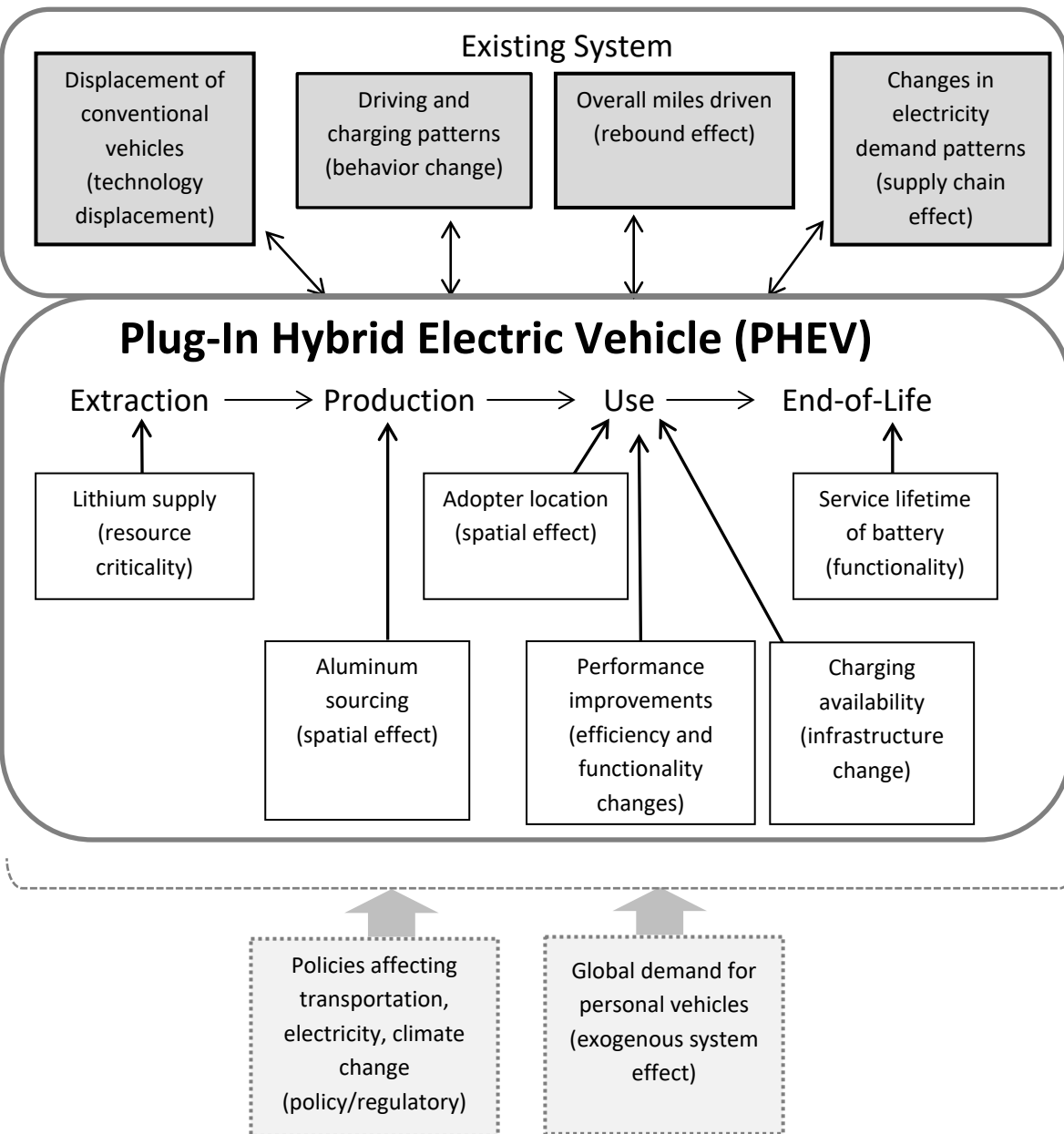


Figure 2. Examples of the ten factors that may impact the life cycle results of a PHEV. Intrinsic factors (located within the PHEV boundary) are directly related to product design and function. Indirect factors (located at the interface of the PHEV and existing system boundaries) affect the LCA according to the technology's interactions with the existing system. External factors (located outside both boundaries) affect the overall system but are independent from the technology's deployment.

Intrinsic Factors

Assumptions regarding *efficiency and functionality* improvements often drive the results of the LCA of PHEVs. The battery's chemistry, mass, volume, expected lifetime, and recharge efficiency impact life cycle results from both the manufacturing and use phases of the vehicle [49, 50].

Spatial effects can have a significant impact on the greenhouse gas (GHG) emissions per passenger-mile [51]. MacPherson et al. conducted a study analyzing region-specific GHG profiles for PHEVs and found that life cycle GHG emissions varied dramatically across the nine regional grids in the United States [52]. The GHG footprint of PHEVs changes according to whether the vehicle is driven primarily in the city, where it takes advantage of the battery technology, or the highway, where the gasoline engine is used. The location where a vehicle is adopted will affect commuting distances, potentially affecting assumptions regarding the overall proportion of electricity and gasoline used. Therefore, the accuracy of an LCA of hybrid vehicle technology can be improved by modeling whether adopters will reside primarily in the city, the suburbs, or an equal mix of both.

The required *infrastructure change* to provide appropriate charging infrastructure and the ability of the grid to adapt to changing demand patterns can affect both the LCA and the potential market penetration of PHEVs. A study analyzing infrastructure impact on alternative fuel vehicles in Portugal reported that infrastructure emissions are responsible for 3.5-7.3% of the overall life cycle impact of fuel cell PHEVs [53].

Resource criticality issues are manifested in PHEVs via the use of lithium, a common component of batteries, which is classified as a scarce metal with a limited global supply. Various studies have modeled the cumulative global lithium demand associated with PHEVs, indicating that global supply is sufficient to meet increased demand from electric vehicle adoption, although there is evidence to suggest that the increase in demand may strain individual reserves or may incentivize alternative lithium extraction methods at some point in the future [33, 54]. Understanding potential implications for scarcity can help inform early recycling infrastructure and improved design choices.

Indirect Factors

The aggregate change in fleet emissions depend on the *technology displacement* effects of PHEVs. PHEVs are likely to appeal to only a certain subset of the population [55]. Therefore, modeling adoption for the appropriate subset of displacement, rather than the average vehicle fleet, can significantly affect LCA results. When a PHEV displaces a conventional vehicle, the potential for GHG emission reductions are significantly greater than when a PHEV displaces a hybrid electric vehicle (HEV), due to the relative fuel economies [49]. Similarly, PHEV displacement of an E85 vehicle running on cellulosic ethanol will have significantly less GHG reductions than if it displaces a vehicle running entirely on gasoline [49].

Driving patterns, length and duration of trips, and driving and charging *behaviors* affect the ratio of electricity to gasoline consumed during the drive cycle, as well as assumptions regarding battery life [49]. The behavior associated with battery charging can change associated vehicle emissions due to a different generation portfolios during peak and off-peak hours [56]. In addition, factors of charging duration (whether the battery is allowed to charge and discharge fully) can affect overall service lifetime of the battery. There is some evidence to suggest that a *rebound effect* occurs with increasing fuel economy of vehicles, yet is unclear if this effect is present in the case of hybrid vehicle technology [57]. PHEVs may facilitate and incentivize *supply chain effects*, such as changes to overall electricity demand,

304 shifting of peak electricity loads, and the ability to act as electricity storage, which can reduce generator
305 emissions of CO₂, SO₂, and NO_x [58].

306 ***External Factors***

307 A variety of *exogenous system effects* have been included in future scenario modeling of PHEVS, such as
308 oil price forecasts and resultant vehicle adoption patterns [51]. In addition, *policy and regulatory effects*
309 that incentivize purchases of alternate fuel vehicles or increase available charging infrastructure may
310 increase potential market penetration. Incentives to support preferential recharge profiles may impact
311 the types of behaviors that lead to favorable environmental profiles [59]. Increased regulations on GHGs
312 may increase PHEV adoption potential and also affect assumptions regarding the emissions inventory of
313 the electricity grid. Renewable portfolio standards or other interventions that affect the electricity
314 sector will also impact the LCA of PHEVs.

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Case Study – Online Commerce

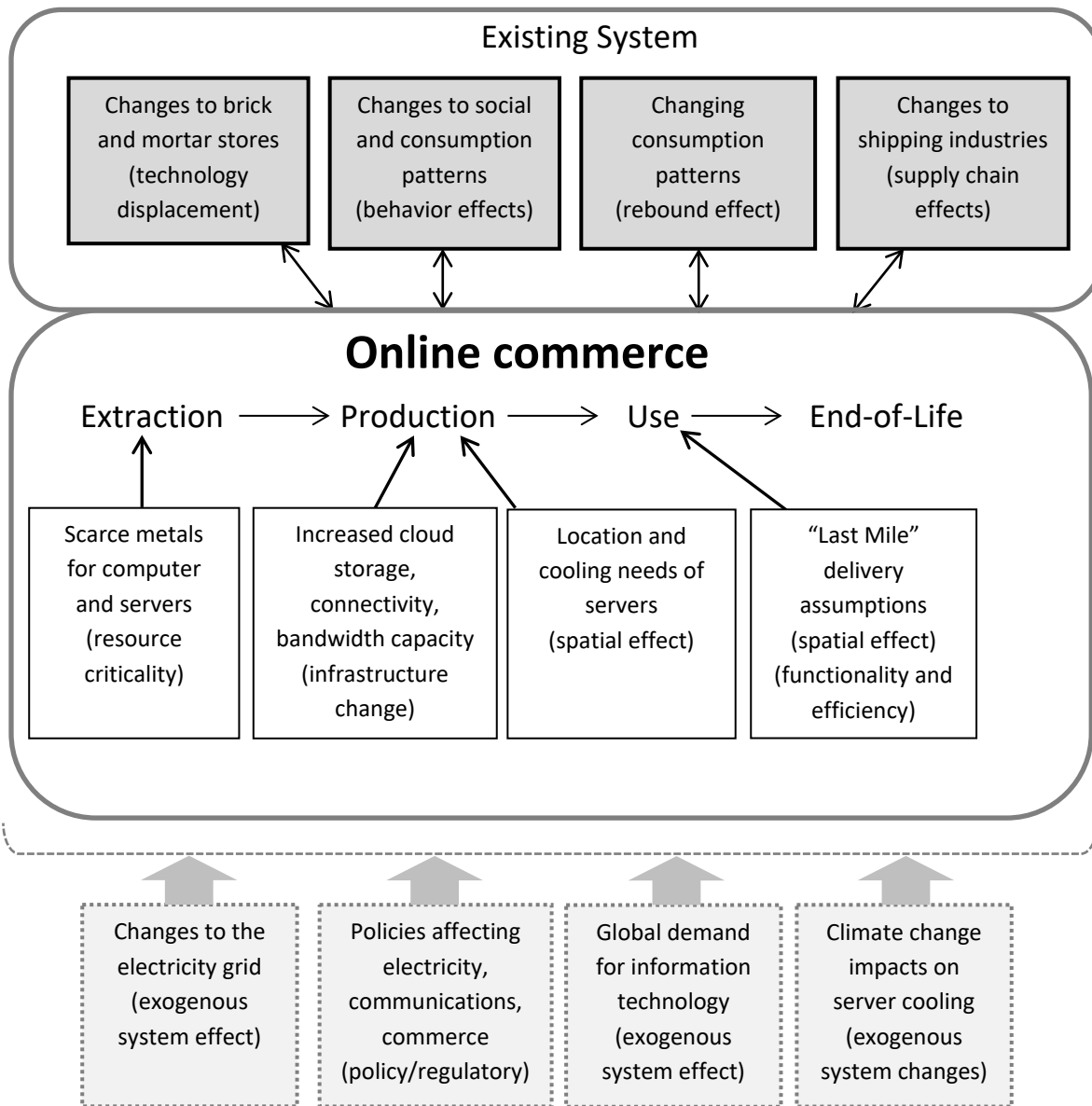


Figure 3 Examples of the ten factors that may impact the life cycle results of online commerce. Intrinsic factors (located within the online commerce boundary) are directly related to product design and function. Indirect factors (located at the interface of online commerce and existing system boundaries) affect the LCA according to the technology's interactions with the existing system. External factors (located outside both boundaries) affect the system but are independent from the technology's deployment.

The PHEV case study demonstrates the multitude of LCA studies that have incorporated some subset of factors associated with the analysis of transformative technologies. The same factors can be applied to any transformative technology, although the relative importance of the factors will vary. Even though there are fewer published studies associated with online commerce, Figure 3 shows the applicability of each of the factors to this technology. Much of the existing research regarding online commerce has focused on the high degree of variability associated with the system's environmental impacts and

analyses concerning the “last mile” problem, which refers to the final leg of delivery between a distributor and the consumer [60, 61]. Many of the other factors within the framework have not received much attention, yet also have potentially significant effects on the LCA of online commerce.

Intrinsic Factors

LCA results for online commerce are highly dependent on intrinsic factor considerations, particularly given the ambiguous boundaries of the technology. Assumptions surrounding the “last mile” of delivery influence *spatial effect* factors as well as the *functionality and efficiency* of the system. For example, the use of mobile phone technology to improve the effectiveness of package delivery could reduce failed delivery attempts and the overall GHG emissions associated with the “last mile” [62]. Increased cloud computing approaches are expected to use data center resources more efficiently [63]. Installation of additional computing capacity will contribute to overall *infrastructure changes* that will impact system performance. Many of the electronics involved in the creation of online infrastructure contain scarce metals, with the potential for *resource criticality* issues [64].

Indirect Factors

Online commerce has the potential to transform society in a variety of ways, so the indirect factors have far-reaching implications for LCA. Shopping online has the potential to induce *behavior changes* that can affect overall consumption patterns. Earlier LCA studies on e-commerce have indicated that LCA results are highly sensitive to assumptions regarding consumer behavior [65]. These changes can lead to *rebound effects* that incentivize increased consumption due to the efficiency in which goods and services can be obtained, as well as *technology displacement* as brick and mortar stores adapt to the evolving consumer market. Online commerce has already initiated *supply chain effects*, particularly with respect to the shipping industry. As one study indicates, shipping companies could realize significant carbon emissions reductions by transitioning to collection-delivery points for failed home deliveries rather than making multiple delivery attempts [66].

External Factors

A number of *exogenous system changes* can affect the environmental impact of online commerce, including changes to the electricity grid, increased global demand for internet access, and increased global populations with greater wealth and the desire to access goods and services from distant locations. Online commerce will also be affected by future *policy and regulatory changes* to a number of sectors including electricity, communications, and commerce.

Discussion

Each of the factors considered in this paper can affect the life cycle results of a transformative technology; however, it is not necessary, or even appropriate, for each of the factors to be included in every LCA of these products. Analysis of a transformative technology is complex, requiring an integrative, interdisciplinary approach to understanding the technology’s potential impacts on the overall system. As with all LCA, the scope of a single analysis should be dictated by the specific research

questions. An example research question for PHEVs might be, “What battery characteristics have the lowest life cycle impact?” To appropriately address that question, a study may focus on factors of efficiency and functionality, resource criticality, and behaviors associated with battery charging. Meanwhile, a parallel study may attempt to address the question, “How will large scale adoption of PHEVs change the GHG emissions of the vehicle fleet?” This type of study would focus on an entirely different set of factors, potentially focusing on technology displacement, charging infrastructure, rebound effects, and adopter location. For each research question, researchers may choose to incorporate spatial factors to understand the sensitivity of results to regional differences or external factors such as potential policy changes. The extent to which each of the considerations will affect LCA results will be technology-specific and these factors should be considered on a case by case basis. For example, it is unlikely that the larger scope of the study will allow detailed analysis of battery performance, highlighting the need for an integrative approach among LCA practitioners. It is important to note that the above research questions require a mixture of intrinsic, indirect, and external factors to inform their respective analyses, regardless of whether the question lends itself to an attributional or consequential approach.

Although all cases are unique, there are some general observations that can be made regarding integration of the identified factors into a transformative technology LCA. Figure 4 categorizes the ten factors according to their expected degree of influence on LCA results and their relative associated uncertainty. The categorizations in Figure 4 result from expert opinion informed by the literature review of prospective LCA in this paper. Figure 4 is intended as a reasonable starting point to discuss the relative importance and difficulty of including each factor into an LCA of transformative technology. None of the factors are classified as having both low uncertainty and low influence, given the difficulty of predicting the future and the sensitivity of LCA results to the assumptions embedded within future scenarios. Factors that are expected to have a large influence on LCA results and can be estimated with relatively low uncertainty tend to be most often included in LCA studies. All factors within this group are intrinsic factors directly related to technology design and deployment.

Some factors are expected to have a relatively minor effect on LCA results, even though they are characterized by a high degree of uncertainty. These include infrastructure change and supply chain effects, which depend on highly uncertain predictions of market penetration but when amortized over a long period of time have a relatively minor contribution to LCA results.

The most challenging section of Figure 4 for LCA practitioners are the factors that are highly uncertain, yet can have the greatest influence on

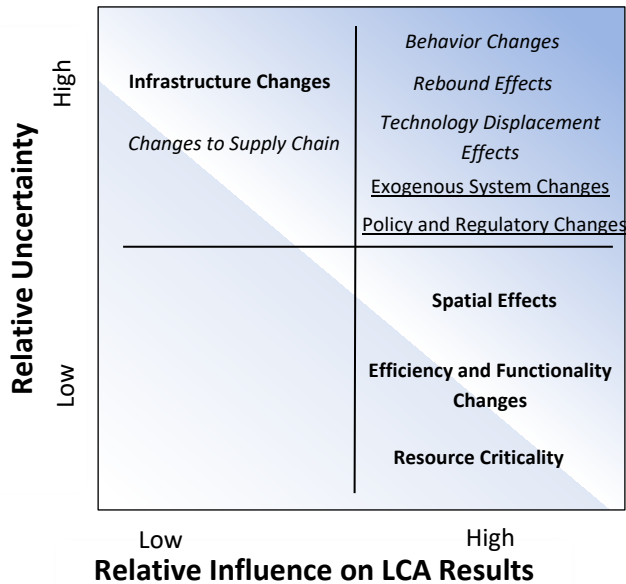


Figure 4. Expected influence on LCA results vs the expected Relative Uncertainty of different factors associated with transformative technologies. Intrinsic factors are in bold; indirect factors are italicized; external factors are underlined.

LCA results. Both of the external factors and most of the indirect factors are included in this quadrant. Some of these factors, such as technology displacement, are considered typical of the consequential LCA approach, but others, such as behavior changes, generally cannot be captured via economic modeling. Understanding transformational technologies in the context of behavioral considerations and the extent to which they displace or supplement existing technologies is incredibly complex. Additional efforts must be directed at understanding how innovations enter the market and how to model the environmental impacts of that transition. Exogenous system changes are extremely difficult to predict and will likely have broad environmental impacts that may affect competing technologies very differently. What-if scenarios and other methods of scenario forecasting may be useful to inform the LCA process to help address these factors that are both highly uncertain yet have a large impact on LCA results [67].

Modeling future deployment scenarios will help the LCA community better contextualize LCA results and inform decisions to incentivize favorable outcomes. Modeling adoption behavior of emerging technologies is difficult due to the large uncertainties associated with end user behavior and potential adoption patterns; however, fundamental design principles show that the early stages of the design phase offer the greatest freedom for improvement, even though uncertainty about the system is also highest. The unavoidably large uncertainty for these systems inhibits the LCA process and disincentivizes undertaking the effort, reducing LCA's usefulness as a decision support tool [68]. Despite the inherent uncertainty, anticipating the consequences of a transformative technology at an early stage may allow for more successful mitigation of future problems. In order to make LCA function as a more effective decision support tool and take advantage of the greatest improvement potential, the LCA community needs to address the challenges represented by these technologies and embrace the inherent uncertainty despite the difficulties presented [69]. By creating frameworks to appropriately analyze transformative technologies, it may be possible to make more effective recommendations for early-stage design and policy decisions. The compiled list of factors is intended to help formalize the process of analyzing transformative technologies so systematic choices can be made according to which factors should be included to appropriately answer a given research question.

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