REAL Supply

TOPIC 5:
Diffusion of technology and ways of working

Authors:
Joe Spearing
Susan Griffin

Part of: The Health Foundation REAL Centre

Contents

Plain English summary

Context

The decision to use a particular tool or way of working is described as a decision to 'adopt' a technology. Diffusion is the pattern made up of a sequence of adoption decisions. This research explores how new tools and ways of working spread throughout the NHS and social care, focussing on the factors which influence decisions to adopt a technology. It investigates why some parts of the system adopt new practices faster than others, and considers the system-wide factors that drive change. We also consider the diffusion of 'disinvestment', which is a decision to stop using low value technologies. The rate of technology diffusion may depend on the motivations of the actors responsible for adopting it, or the characteristics of the technology itself. Systems that are slow to adopt new valuable ways of working, or slow to move away from low value technology may be able to make adjustments that improve overall benefits.

Knowledge Gap

Existing research often focuses on how a particular example of a technology has spread. This narrow focus tells us little about how to build a health and care system that will be able to make the best adoption decisions as new developments emerge. Developing a way to categorise different technologies is difficult, but it would help us understand and use economic research in this area. Existing research does not tell us much about how the speed of adoption and disinvestment impacts overall population health and care outcomes and on inequality in outcomes.

Value

This research focuses on the speed and unevenness of technology diffusion across the NHS and social care with the aim to estimate the benefits forgone from imperfect diffusion. This research will explore "market failures" and system characteristics that can lead to inefficient adoption and disinvestment rates and analyse what can be done to change the speed of adoption.

Impact

This research aims to identify barriers to the spread of beneficial health and care innovations, informing policies to improve efficiency, quality of care, and population outcomes. Combining new knowledge on what can be done, with new knowledge on the payoff from changing the speed and spread of adoption, will provide stakeholders with insight into valuable ways to improve system performance.

Defining the problem

In health and social care, technology plays an important role in driving quality improvements and cost (Laudicella et al., 2021). We refer to technology in the broad economic sense of how inputs are combined to produce output, and so in addition to physical and digital technology, we also include "ways of working": service innovations in the way care is organised and delivered. To the extent that technology affects efficiency and sector outcomes and cost, studying the factors which drive its use is important for improving health and care policy.

This pathfinder studies the *diffusion* of technology and ways of working in English health and social care economy. By diffusion we mean the rate at which different actors within the economy adopt new technologies and ways of working. Diffusion is something that is assessed at the population or system level, by examining patterns of use across the system and across time. However, the English health and social care economy is complex, with a large number of actors with differing information and incentives. The dependence of one actor's adoption decisions on those made by others relates to how actors are connected within networks. Thus, understanding patterns of diffusion requires an understanding of the different actors and the different contexts in which they operate. Given the complexity of the system, it is perhaps unsurprising that we observe a dispersion in the adoption of technology within the healthcare economy, with some actors adopting new technology and ways of working quickly, and others deferring adoption until long after others have established its use.

"The English health and social care economy is complex, with a large number of actors with differing information and incentives."

Understanding the different decision processes and incentives present can help us understand why the health and care system functions as it does with respect to diffusion of technology, and how it may be possible to better align activity with policy goals. For the most part, incentives in the public health and social care system are determined by government contracts. Some incentives can act primarily via costs, for example in the way actors receive income. Common financial incentives include capitation payments for GPs, and National Tariffs, both of which are fixed payments for a given type of patient or activity. For actors that are responsible for managing budgets these payment systems can create the incentive to control costs at the expense of improving quality (Ghandour et al. 2022). Where this is the case, the nature of these payment schemes may bias use of technology and ways of working towards those which reduce costs. Conversely, actors that do not manage budgets may be insensitive to such payment mechanisms. For these actors, and for incentives that act primarily on quality such as publicly available provider ratings, there may be bias towards use of quality improving technology regardless of cost. Capitation and provider ratings are not specific to any particular innovation. However, some incentives actively target specific technologies, for example funds allocated to promoting the rollout of electronic records[1] and pay-for-performance schemes that reward pre-specified activities such as clinical best practice. Better understanding of diffusion may be informative to knowing where and when their use is warranted.

1 For example NHSX Digitising Social Care Fund

Incentives can be equity focussed, for example with the aim of reducing variation in adoption. The National Institute for Health and Care Excellence (NICE) was established to reduce variation in access to good quality care; it produces guidance on best practice, some of which gives patients legal recourse to demand that the NHS fund the recommended care. This may increase actors' information regarding some technologies and may bias use towards those that have received attention from NICE at the expense of other cost or quality improving options outside of NICE remit. Despite these policies, there is evidence of failure to ensure widespread adoption of even NICE recommended technology (e.g., Whyte et al., 2014).

The counterpart to the diffusion of adoption is the way in which technology that has proven not to be of value is removed from use. The term 'adoption' is most often seen in conjunction with concern about under-diffusion of high value care, while the term 'disinvestment' to describe a change in way of working is typically applied to the decision to stop using low value technologies that are in established use. Despite the theoretical complementarity of adoption and disinvestment, they may be characterised by different decision processes and are often addressed separately in research and policy (van Bodegom-Vos et al., 2017). If the factors that influence adoption and disinvestment are different, this may suggest asymmetric consequences to under- versus over-diffusion.

We discuss what factors influence the rate of diffusion, whether and where the rate of diffusion is likely to be faster or slower than the social optimum, and whether the system optimally selects which innovations diffuse the fastest. It is notable that, in healthcare especially, certain innovative technology is the product of firms and organisations that derive income from its use. Private expenditure on advertising and promotion can therefore raise awareness of technologies, such as patented pharmaceuticals, and promote their use over other more cost-effective care (Schwartz and Woloshin JAMA 2019). In contrast, service innovations and other technologies without commercial backers or champions may diffuse more slowly or fail to launch. In comparison to research and development funding, the NHS spends a relatively small proportion of its budget on facilitating the spread of innovation through initiatives such as the Health Innovation Network (Collins, Kings Fund, 2018). Of key importance is the possibility that diffusion of technology in publicly funded sectors can be, overall, bad for welfare, since spending is effectively subsidized (Dunn, Fernando and Liebman, 2024). In this case we may be interested to know which system factors promote specificity of adoption. Assessing the optimal speed of diffusion may require better understanding of the trade-off between benefits from accelerated access, increased risk and the cost of uncertainty (Forrest et al. 2024). Conversely, a system that is slow to adapt through adoption and disinvestment may be forgoing sizeable welfare gains (Frankovic, Kuhn and Wrzaczek 2020).

The diffusion of technology is made up of a sequence of adoption decisions. We will touch on the factors which affect individual actors' decisions to adopt technology and ways of working. However, our focus is on the *diffusion* because we emphasise the rate of change in use of technology and ways of working and the unevenness of the use of technology across the health and care economy. Our concern is with unwarranted variation, in recognition that the social optimum need not equate to immediate nor complete diffusion. We are also agnostic about which actors' decisions are policy-relevant. When we talk about the diffusion of technology and ways of working, we will refer to diffusion amongst different actors, including GP surgeries, providers such as NHS trusts and social care providers, commissioners (i.e., ICBs), and individual clinicians. Similarly, we aim to be inclusive of different types of technology. The factors influencing the diffusion of technology may be different depending on the actors responsible for adoption and the nature of different technologies, but case studies may offer little in terms of insight. The research innovation this pathfinder seeks is how far economics can contribute to understanding system-level factors and structural conditions which affect the pace of change in use of technology over the long-term.

Relevant economic considerations

> **"An actor adopts the innovation if the expected benefit of adopting the technology is higher than the cost."**

The goal of the health and care system is generally accepted to be the improvement of health and care outcomes in the population. From this we can characterise a system-level objective function for the optimal diffusion of technology, wherein ways of working should be adopted to the degree that they improve population health and care outcomes. In practice, diffusion of technology and ways of working are composed of a series of individual decisions to adopt innovation. Hence, we must focus on the decision of an actor within the health and social care economy to adopt a particular technology or way of working. Economics has a ready-made framework for modelling this decision: an actor adopts the innovation if the expected benefit of adopting the technology is higher than the cost.

The benefits of adopting the innovation depend on the *incentive structure* in which actors operate. This insight reveals an important role for government policy in influencing the diffusion of innovation. Many actors within health and social care in England are paid in part through fixed payments, such as capitation or national tariffs, which means that the benefits of new innovation do not directly or immediately modify their income. This effect may blunt incentives to introduce quality-improving technology. Activity based payments can incentivise adoption if set appropriately, but rigidity in such payment structures is often cited as a factor that inhibits disinvestment as actors seek to maintain income. On the other hand, many actors in health and social care may be altruistically motivated, introducing new technology and ways of working to improve quality because of their personal satisfaction from seeing improvements in care.[2] Some attention has been paid to how different incentives may interact, for example whether altering extrinsic motivation to adopt (e.g. payment by rewards), crowds in or crowds out intrinsic motivation (Frey Rationality and Society 1994). The incentive structure may vary by type of technology, as illustrated by Zweifel (2021) using the categories of product, process and organisational innovation. Product innovation increases current patients' willingness to pay via the provision of new valued attributes, which in turn benefits physicians through increased demand for their services. Process innovation improves technical efficiency, but impact on demand is dampened by cost savings being shared between insurers and patients. Organisational innovation relates to vertical integration, and due to impact on autonomy and job roles can be resisted by incumbents and beneficiaries of the present structure at the expense of potential future beneficiaries. This implies that process and organisational innovation may diffuse more slowly than product innovation.

In addition to the incentive structure, *features of technology and the environment* will affect adoption decisions. Firstly, uncertainty about the likely costs and benefits of adopting innovative technology or ways of working is likely to affect the expected benefit of adoption. Assuming that agents differ in their taste or capacity for risk in adopting technology, certain agents will be faster to adopt novel

2 We review the literature on physician motivation in the pathfinder, "The consequences of widening the recruitment pool".

technology, and other agents will delay until there is greater evidence. The distribution of tolerance for risk will be a key determinant of the pace and pattern of diffusion throughout the system. Secondly, *information provision* is also likely to affect decision making about adoption of innovations. In order to adopt a new technology or way of working, agents must be aware of them, their costs and benefits. The rate of information diffusion and extent of information frictions between actors across the health and care economy will therefore also have an effect on the rate of diffusion of technology.

There are several potential "market failures" which might cause the rate of diffusion of technology or ways of working to be different from the rate which maximises social welfare. Firstly, externalities occur when there is an effect of economic behaviour on third parties. In many technologies and ways of working, there are positive externalities on other agents from adoption. For example, *network externalities* occur when the benefit of a technology depends on how many people have already adopted the technology (e.g., electronic records). Other types of positive externalities include "learning by doing", where the specific training afforded by use of an innovative practice generates lessons which others can apply. Where these externalities are present, individual actors will adopt technology more slowly than is optimal.

Secondly, there are pervasive *principal-agent* problems in health and social care. Principal-agent problems occur when an agent is contracted to perform an action on behalf of a principal, but their preferences are not fully aligned and agent actions cannot be perfectly observed. In these circumstances, principals may struggle to design incentive structures which entice agents to behave according to the principals' preferences. As we have already discussed, policymakers have adopted several policies to incentivize adoption of technology and ways of working. If principal-agent problems are pervasive, then we will tend to find that new technologies and ways of working which are not explicitly incentivized within the health and social care economy diffuse more slowly than is optimal. On the other hand, health professionals may adopt ways of working which improve quality but are not cost-effective. In this case, the principal-agent problem will lead to diffusion of technology which is too quick. The adoption of some technologies requires action from multiple actors, and here *game theory* can highlight how unilateral decision making can lead to the failure to adopt technologies that, with cooperative action, would improve welfare. Behavioural economics offers insight into where actors may depart from the rationality assumed in economic theory. Loss aversion, status quo bias and the endowment effect are particularly relevant to understanding why the decision process for disinvestment can differ from that for adoption (Hofman 2021).

Finally, *credit constraints* may affect the pace of adoption of technology with high upfront costs. To the extent that agents within the health and social care sector are credit-constrained, we will find that the diffusion of technology which has large upfront costs will be inefficiently slow.[3] More generally, the proportion of fixed costs and the shape of the marginal cost function may interact with the diffusion curve. If the cost of a technology is a reducing function of throughput, then early adopters would face higher costs than later adopters. If prices are based on the average cost this might prevent the initiation of adoption. Disinvestment may also stall for technologies where a certain level of disinvestment is required before fixed cost elements can be reallocated.

Overall, the implication of these market failures is that the diffusion of technology can be inefficient, and that social welfare can be improved by intervention. We may also conceive of policy options

3 We explore liquidity constraints in the pathfinder Incentives for long-term investment

that alter the context or environment of the adoption decision in order to mitigate the influence of externalities. We may think of potential policy actions in terms of specific incentives that aim to correct for the misalignment caused by externalities. While a lot of policy attention has been paid to the potential welfare loss from slow diffusion, it is possible that in some areas the health and care economy adopt technology at too fast a rate. Dunn, Fernando and Leibman (2024) show in a US context that the diffusion of some drugs is adverse for welfare, i.e., the cost to the consumer is higher than the welfare gains. This outcome is possible because health insurance makes consumers price insensitive as they do not face the full cost of the medicine they use.

Terminology

For the purposes of this pathfinder we adopt some specific terminology. We marry taxonomies developed around healthcare innovation and digital technologies with economic terminology.

An actor or an agent is defined as an entity within the system who must alter their behaviour to implement a particular way of working. For example, this may be a nurse that could adopt a brief smoking cessation intervention by starting to deliver it to patients. Equally it could be a project manager within a hospital that uses funds to purchase and organise the installation of an electronic system for recording activity. Adoption may require more than one type of actor to alter their behaviour. A policy maker or a principal will be defined as an entity that can alter the system in which the actors operate. This could include entities such as NHS England that determine national tariffs, or the governing political party who may determine the remit of different Departments.

In April 2024 the Department of Health and Social Care published a medical technology innovation framework which defined three different types of innovation: incremental, transformative and disruptive.[4] This taxonomy is useful to explain to which the degree aspects of the system are altered by the innovation. In its classification of digital health interventions, the World Health Organisation defined groups according to the primary user of a technology: interventions for clients, interventions for providers, interventions for system or resource managers, and interventions for data services. This is useful to explain the types of actors that must alter their behaviour to adopt an innovation. Considering these taxonomies in line with the pathways through which market failures and levers may operate will help us frame the existing literature. Table 1 gives an example of a possible taxonomy of actors and technology types.

4 https://www.gov.uk/government/publications/medical-technology-innovation-classification-framework/medical-technology-innovation-classification-framework

REAL Supply

Table 1: Taxonomy of actors and technologies

	Incremental	Transformative	Disruptive
Clients	NHS App	Home ECG monitor	
Providers	Pay for performance		
System and Resource Managers			Integration of services and budgets
Data Services		Within system move from paper to electronic records	Linked data system across primary and secondary care and social care

What is already known?

A systematic review commissioned by the UK Department of Health revealed a wide spread of disciplinary areas that have contributed evidence to the study of diffusion of technology, although notably economics was not among the 13 listed areas (Greenhalgh et al., 2004). In this pathfinder we focus on three strands of existing literature which help understand the problem of the diffusion of technology within the health and care system. Firstly, empirical management science literature has developed methods of modelling the pace of adoption of technology over time. Secondly, there is a mostly reduced-form literature in health economics which investigates factors which promote the adoption of technology. Thirdly, a few papers have sought to model the steady adoption of certain technologies within healthcare.

Modelling the pace of adoption of technology over time

Technological diffusion can be micro-founded in multiple different ways. Young (2009) explores three different kinds of model: a model which explains technology adoption analogously to an epidemic (where a person's hazard for adopting a new technology depends on exposure to current adoption); social influence, where each person adopts a technology once a threshold of adoption within the population has been passed; and social learning, where each person uses Bayesian updating to inform their beliefs about the value of technology by observing others. Each set of modelling assumptions can generate observed patterns of aggregate adoption of consumer technology.

Much of the management literature has followed Bass (1969) in seeking to explain consumer adoption of new technology as resulting from both innovation and imitation (making analogy to an epidemic). Innovation occurs when consumers who do not currently use the technology decide to adopt the technology spontaneously. Imitation occurs when consumers are exposed to earlier adopters and is proportional to existing adoption rates. These two forces explain the commonly observed S-shaped curve in adoption, where the rate of usage first accelerates and then decelerates.

Easingwood et al. (1983) generalise the Bass model to include non-uniform influence of existing adoption. Letting f be the current share of the population which has adopted the technology, and f be the rate of technology adoption. They propose:

$$df/dt=(p+q(f/F)^{\delta})(F-f)$$

where p is the strength of innovation, and is the strength of imitation. δ adjusts for the fact that early adopters might have different levels of influence on the rate of diffusion to late adopters. We can see from this equation that the influence of innovators will tend to zero as the rate of adoption approaches its terminal value. On the other hand, the strength of imitation will increase as f increases for low values of f.

The Bass model has mostly been applied to explaining and forecasting the adoption of consumer technology, such as washing machines, televisions, and smartphones. To improve forecasting, researchers have extended the model to include mean-reverting error terms (Kanniainen, Makinen, Piche, and Chakrabarti, 2011) and additional covariates (Jain, 1992). Several researchers have embedded important problems for firms and industries in the Bass model such as optimal monopoly pricing (Bass, 1980) advertising spending (Dockner and Jorgensen, 1988), and supply chain adaptation (Jones and Ritz, 1990).

In order to consider the welfare properties of the rate of technological adoption, technology adoption must be modelled using individual level utility ('agent-based simulation', Kiesling, Günther, Stummer, Wakolbinger, 2012). Decker and Gnibba-Yukawa (2010) consider an individual deciding whether to adopt technology this period or wait until next period, forming expectations over price and deriving utility from having adopted the technology and disutility from spending. They show that with type-1 extreme value distributed error terms the probability of a person adopting the technology each period can be expressed as a logit function and estimated using non-linear least squares. An important study using individual-level utility which can have applications in the adoption of technology in healthcare systems is (Katz and Shapiro, 1986). They study technology adoption in a multi-period game with network externalities. They show that the Nash equilibrium without coordination does not lead to a Pareto efficient outcome, but there are government policies such as taxes and subsidies that can.

Investigating which factors promote the adoption of technology

Actors within health and care systems- hospitals, GP practices, individual doctors, care home providers, or ICBs- make decisions about which technologies and ways of working to adopt and abandon in the presence of varying financial incentives, information and motivations. A large empirical health economics literature explores the effect of variation in these factors.

Peer effects affect the adoption of technology: it may be easier to learn new techniques from peers, or agents may be affected by norms. Escarce (1996) finds that surgeons are more likely to adopt laparoscopic cholecystectomy when another surgeon in the same hospital adopts it. Iversen and Ma (2022) study the rate of Norwegian GPs' adoption of recommended checkups for patients with type 2 diabetes. They find using a movers design that GPs are influenced by the rate of adoption in their municipality. Molitor (2018) finds a similar effect when cardiologists migrate in the US: cardiologists who move to regions where the treatment norm is for more aggressive and invasive treatments increase the use of aggressive treatments. The effect of moving to a region which has less aggressive treatments is smaller, however, suggesting a smaller peer effect on abandonment of technology. Liu and Gupta (2012) show that the probability of adopting a new drug is positively associated with geographical proximity to doctors who have already adopted the drug. Barrenho, Miraldo, Propper, and Walsh (2021) study adoption of laparoscopic colectomies in the English NHS. They find that surgeon connectivity- the number of doctor colleagues a Surgeon has had- is associated with adoption of laparoscopic surgery, but is not associated with use, conditional on adoption. Barrenho et al. (2025) find that peer networks play an important role in the diffusion of the use of keyhole surgery for colorectal cancer. They show that on average, an increase in a physician's network increases the share of operations performed with keyhole surgery, but also that there are identifiable "key players" within the network, exposure to whom has an especially large effect on a physician's usage of keyhole surgery.

In many healthcare systems, policymakers use financial incentives to encourage the adoption of technology and ways of working. Klausen, Olsen and Risa (1992) study the adoption of dry-chemical laboratory equipment by Norwegian GP practices, using a profit function which reflects their financial incentives. They find that existing reimbursement incentivizes slow adoption of the new technology. Policymakers often design payment systems to incentivise particular behaviours, including meeting particular standards or adopting particular ways of working (Doren et al., 2006). Some of these policies have been shown to be effective: Scott, Schurer, Jensen and Sivey (2009) study a practice incentive program in Australia which introduced explicit financial incentives for meeting standards of care for patients with diabetes, finding that participation in the program increased the likelihood of meeting standards of care. Walker, Pretis, Powell-Smith, and Goldacre (2019) study financial incentives for following recommended prescriptions in the NHS, finding that financial incentives have a stronger association with adoption of the new guidelines than the recommendation itself, on average. Finally, the effect of competition can vary depending on the context: while Iversen and Ma (2021) find no association between competition and adoption of standards in a Norwegian context, Hamilton and McManus (2005) study adoption of cutting edge Assisted Reproductive Technology (ART) in the US, finding that competition increases the probability of adoption.

Researchers have also studied the characteristics of physicians, patients and guidelines that promote adherence to guidelines. Abaluck, Agha, Chan, Singer, and Zhu (2020) study adoption of the CHADs score for assessing risk associated with the use of anticoagulants for atrial fibrillation. They find that awareness of the CHAD guidelines (as measured by reference in doctor notes) predicts increased usage of the guidelines in decision-making. Guidelines are more likely to be followed when they are clear, non-controversial, evidence-based, and do not provoke adverse patient reactions (Grol et al., 1998). Education campaigns and mass media campaigns can be effective in increasing rates of adherence to guidelines (Grol and Grimshaw, 2003). Physician skill can affect responses to changes in guidelines, with Wu and David (2022) showing that physicians who had lower complication rates in open hysterectomies abandoned MI hysterectomies at a faster rate when FDA recommendations changed. Finally Finkelstein, Persson, Polyakova, and Shapiro (2022) study whether patient access to medical information changes adherence. They find that patients with a close family member who is a doctor experience *lower* adherence to recommended standards of care, suggesting that their privileged access to information might cause them to request deviations from official guidelines.

In a study by Grimm et al (ViH 2018) the Bass model was combined with methods for expert elicitation to forecast the diffusion of a new preterm birth technology. In one scenario they also explored the role of further evidence in elicited Bass model parameter values.

Compagni, Mele and Ravasi (2015) present an important rejoinder to the paradigm of economic theory. They use a series of qualitative interviews to study Italian hospitals' decision to adopt robotic surgery technology. They find an important role for early, "exemplary" adopters showing the potential efficacy of robotic technology. Importantly, however, they find that the decision to adopt robotic technology is driven by the identity of adopters- wanting to be seen as "high-tech" hospitals, or establish themselves as trailblazers- rather than beliefs about efficacy. At a later stage, adoption is driven by patient demands: hospitals do not want to be seen as laggards, as patients typically disapprove. This narrative demonstrates that factors beyond patient outcomes, cost, and financial incentives might drive technological adoption.

Modelling adoption of technology in healthcare

Very few papers have modelled the adoption of technology in healthcare. Klausen, Olsen and Risa (1992) model GPs as dynamic profit-maximising entities (see above). However, to our knowledge, the most detailed model of technology diffusion in the healthcare sector comes from Skinner and Staiger (2015).

In Skinner and Staiger's (2015) model, hospitals choose both inputs, x_{it}, and the rate of technological diffusion π_{it}, defined as the rate at which it closes the gap between its level of technology and the frontier. The hospital's objective function is a weighted average of patient outcomes, the costs of inputs, and the cost of increasing the rate of technological diffusion. Where y_{it} is a measure of patient outputs, their model implies that:

$$y_{it}=a_t^*-\alpha[(1-\pi_i)/\pi_i]+\beta x_{it}+u_{it}$$

Here a_t^* is the technological frontier, α is its growth rate, and u_{it} is an error term. Skinner and Staiger estimate this model using heart attack survival rates and innovations in heart attack treatment technology.

Frankovic, Kuhn and Wrzaczek (2020) build upon Skinner and Staiger's model to study the macroeconomic consequences of imperfect diffusion. In doing so they first assess whether innovation induced increases in healthcare utilisation are welfare improving, before using this model to infer the potential value of policies to alter the rate of diffusion. Their analysis suggests that medical progress has been welfare-improving across the population. They find that perfect diffusion, defined as the immediate adoption of the frontier technology by all providers, would further increase the health expenditure share and with it life expectancy. They calculate the compensating variation to infer that all cohorts would be willing to forgo consumption in order to experience these gains.

To our knowledge, however, there is no existing research which estimates this kind of model in an English context, or incorporates the rich features studied in the reduced form work such as externalities, information frictions including principal-agent problems, and the precise incentive structure of the English health and social care economy.

Characterising systems and technology

Studying diffusion of technology within the health and care sector will rely on measurement of the technology in use and the characteristics of the system in terms of the factors outlined in this document. The organisational determinants of diffusion require information on a range of provider characteristics outlined in previous studies (Greenhalgh et al., 2004). Social network analysis can be used to map network structures so that density and the role of different actors within the network can be analysed in conjunction with models of diffusion. Wang et al. (2025) apply this approach and use community-based snowball sampling to describe a network structure of integrated public health. Using this information they find support for the hypothesis that centrality is linked to the ability to procure and provide resources to manage COVID-19. Allcock et al. (2024) use annual reports published by CCGs to characterise variation in digital capability across providers. They apply a taxonomy derived from options theory to assign digital technologies identified in the annual reports to themed groups, subdivided by technology use case. They then use clustering to differentiate providers in terms of the technology themes. Zweifel (2021) takes a list of 12 healthcare innovations and categorises them according to whether they relate to product, process or organisational innovation. This approach of using a theory founded taxonomy of technologies contrasts with other more simplistic approaches such as the Innovation Scorecard for the NHS that group technologies by disease area.

Where are the gaps?

In summary, there is a rich empirical literature which models the factors which drive the diffusion of consumer technology, but this has not in general been extended to the study of healthcare, and even less so to social care. Much of the empirical health economics literature uses reduced form econometrics to study the effect of peers, financial incentives, and information in the adoption of technology in specific instances. These findings contribute valuable policy insights, but do not necessarily generalise about the factors which affect system-level technology diffusion.

To our knowledge no researchers have formally modelled technology adoption in an English health and social care setting. This limitation has two implications: firstly, whether the factors identified in this pathfinder- the role of different financial incentives, externalities, principal-agent problems, upfront costs, and uncertain benefits- play an important role in determining the diffusion of technological change. Secondly, the existing health economic research, unlike the formal modelling in the diffusion of consumer technology literature, does not allow for researchers to assess whether technology diffusion is faster or slower than optimal.

"An actor adopts the innovation if the expected benefit of adopting the technology is higher than the cost."

A final limitation of the existing literature is that almost all studies study particular technologies or ways of working, e.g., a new drug, or a new screening system. Lessons about the diffusion of technology and ways of working from these studies therefore rely on an assumption that the findings are not specific to the technology studied. In order to discuss the generalizability of findings about a particular technology, researchers must take a stand on the factors which are likely to influence the diffusion of technology and how the technology they study compares to typical types of technology on these dimensions. Kalyani et al. (2024) is a seminar paper which advances beyond case studies to consider the diffusion of technology in general. Their methodology identifies discrete examples of technology using multiple word groupings which appear in patents and then confirming that these word groups refer to technology using wikipedia. They are able to trace these technology markers through their reference in earnings calls and job advertisements. This approach facilitates important insights about the diffusion of technology, including the length of time it takes for full diffusion (around 50 years) and the geographical concentration of the invention of the most important technologies. This paper is unusual in advancing beyond the previous literature to make more general claims about the diffusion of technology *in general*. However, their conclusions may not apply in the specific case of the English healthcare economy, which has a somewhat unique regulatory framework.

One approach to considering technology within healthcare is to categorize types of technology across dimensions which are relevant for the rate of diffusion. An alternative is to operationalize how advanced technology and ways of working are within a particular unit (e.g., a hospital or an ICB). Skinner and Staiger (2015) develop a measure based on US hospitals' usage of cutting edge heart-attack medicines which measures the extent of hospitals' proximity to the technological frontier. Similar approaches in an English context may be viable by using metrics of innovation capability to characterise different units. This approach may be challenging to extend to less measurable aspects of health and social care and settings in which observational data on specific care practices is scarce. However, to our knowledge a more generalised measure of adoption of technology which covers a range of technologies and ways of working does not exist.

What is the opportunity for the research unit?

The analysis in this pathfinder suggests a set of potential research questions, the answers to which would be of direct policy relevance to the long-term organisation of the health and care sector. Firstly, we might investigate how the rate of diffusion of technology and ways of working differs across different types of technology. For example, we may find that technology and ways of working which are expensive to implement but improve quality diffuse at a different rate than technology which is cost-saving; or we may find that technology which has large upfront costs is adopted more slowly. Using a version of the Bass model, we may investigate which kinds of technology experience the most "imitation". The answers to these questions would inform policymakers about the likely incentives for adoption of different kinds of technologies, and the return to public investment in new technology (since investment in early technology will crowd in greater adoption for technologies which have higher levels of imitation).

Secondly, we could explore what likely barriers exist to faster diffusion of technology. We have hypothesised several barriers, including principal-agent problems, network externalities, information frictions, and credit constraints, might prevent faster adoption of technology. Measuring the extent of these market failures would be an important research project which would help policymakers to assess how far from optimal then diffusion of technology and ways of working is within English health and social care.

Finally, in common with much of the literature cited in this paper, we may select certain key technologies and ways of working and explore their diffusion within the English health and social care economy. These case studies can be illuminating about the factors which affect technology diffusion. To the extent that we use particular technologies as case studies, we will select technologies and ways of working which are either key to the functioning of health and social care, or representative of particular ways in which technology diffuses. For example, we may study the diffusion of electronic records, which are a vital prerequisite for modern healthcare organisation, and also illuminates the role of network externalities in technological diffusion. Alternatively, studying the diffusion of key policies such as integrated care might provide important lessons about how coordination between healthcare actors might limit the diffusion of ways of working national policymakers promote.

There are a number of challenges which make this research agenda highly ambitious. The first relates to data: in order to estimate rates of diffusion of technology, we need to observe technology adoption. The quality of data on technology adoption varies significantly depending on the nature of technology. For technology such as drugs, data on prescriptions make it relatively straightforward to assess the extent of adoption (e.g., Walker, Pretis, Powell-Smith, and Goldacre, 2019). On the other hand, diffusion of ways of working is not readily observable, since we typically cannot observe behaviour at this level. Researchers have tended to measure proxies for ways of working, e.g., measuring the employment of link workers instead of the social prescribing (Wilding et al. 2024). There are a number of innovations which may be especially difficult to measure in this way, e.g., integrated care. Finally, there are variations in practice which are not captured by notional adoption of technology. For example, the fact that a provider has formally adopted electronic records does not imply that its staff make appropriate use of them.

Secondly, our research agenda will need to define a universe of technologies and innovations to study. In practice, this universe will be limited by observable data (see the previous paragraph). However, in addition, we will need to define clear criteria for which technologies and innovations are most likely representative of relevant healthcare technology, in order to justify the generalizability of our conclusions.

The latter is also an opportunity to define a theoretically informed typology of healthcare technologies which is based on assumptions about rates of diffusion. For example, we may consider key axes such as:

1. Cost-saving vs quality improving: We have speculated that certain actors within the NHS (GP surgeries) are more likely to adopt cost-saving innovations, while others (such as physicians who do not cost-share) are more likely to adopt quality-improving innovations
2. Technology vs organisation: changes in the adoption of technology (e.g., a new drug, or a different use of an existing procedure) carry different expected risks with them than changes in organisation, which tend to have large upfront costs. We might therefore expect there to be differences in the rate of diffusion
3. Incremental vs disruptive: incremental changes might include using existing technology in a new way and changing role responsibilities, whereas disruptive changes are more likely to include the use of new technologies or more comprehensive reorganizations. The latter are likely to have higher upfront costs and perceived risks.

Table 2 shows an example of how this typology might be understood. In each category, we give examples of the kind of innovations that typify them. One opportunity for the REAL unit is to develop a typology founded in economic theory, including ways of measuring adoption of innovations of each type. Doing so would address a key challenge in the existing literature.

Table 2: Example typology of technologies and ways of working

	INCREMENTAL		DISRUPTIVE	
	Technology	**Organization**	**Technology**	**Organization**
Cost-Saving	Recommendations to abandon ineffective treatments	Use of physician associates	New drugs	Integrated care
Quality improving	Changes in recommendations	Screening programmes	Electronic Health Records	Social prescribing

Conclusion

Technology and innovation play a vital role in the efficient and effective delivery of health and social care. Given the fast pace of technological change and the cost pressures the health and social care system faces over the coming decades, ensuring socially beneficial usage of technology and ways of working is vital.

This pathfinder has considered the complex policy and research questions relating to the diffusion of technology and ways of working throughout the health and social care economy. To summarise, these are: what factors affect the rate of diffusion of technology through the health and social care economy? What is the effect of policy on the rate of diffusion of technology through the health and social care economy? And is the rate of diffusion likely to be faster or slower than the social optimum?

We have set out a series of factors likely to affect the diffusion of technology and ways of working. Firstly, we argue that the nature of the financial incentives facing different actors may affect the adoption choices they make; agents who benefit from profit-sharing- such as GPs- are likely to prioritise cost-saving technology over quality-improving technology. It follows that the kinds of innovations which are adopted by profit-sharing agents may diffuse faster if they are cost-saving. Secondly, we have pointed to the role of positive externalities of technology. We have argued that innovations which have network externalities, or exhibit learning-by-doing, are likely to diffuse more slowly than innovations which do not. Thirdly, we have pointed to the potential role of uncertain benefits and slow information provision in affecting the pace of diffusion.

In our survey of the existing literature, we find that researchers have extensively modelled the factors which promote faster diffusion of technology in a consumer setting. Additionally, there is a large reduced-form health economics literature which explores how factors such as peer effects and financial incentives affect the adoption of specific technologies. There is, to our knowledge, no research which systematically analyses the factors which affect diffusion of technology and innovation within health and social care and asks whether the rate of diffusion is likely to be optimal from an efficiency perspective.

There is therefore scope for an ambitious research programme which assesses the diffusion of technology and ways of working within English health and social care, with a focus on the factors that increase or decrease adoption. We have laid out potential ways of approaching this question, and the challenges researchers are likely to face.

References

Laudicella, Mauro, et al. "Age, morbidity, or something else? A residual approach using microdata to measure the impact of technological progress on health care expenditure." *Health Economics* 31.6 (2022): 1184-1201.

Ghandour, Ziad et al. "Investment and quality competition in healthcare markets." *Journal of Health Economics* 82 (2022): 102588.

Whyte, Sophie, et al. "Getting cost-effective technologies into practice: the value of implementation. An application to B-type natriuretic peptide (BNP) testing in diagnosing chronic heart failure." (2014).

van Bodegom-Vos, Leti, Frank Davidoff, and Perla J. Marang-Van De Mheen. "Implementation and de-implementation: two sides of the same coin?." *BMJ quality & safety* 26.6 (2017): 495-501.

Schwartz, Lisa M., and Steven Woloshin. "Medical marketing in the United States, 1997-2016." *Jama* 321.1 (2019): 80-96.

Collins, Ben. "Adoption and spread of innovation in the NHS." (2018).

Dunn, Abe, Lasanthi Fernando, and Eli Liebman. *How Much Are Medical Innovations Worth? A Detailed Analysis Using Cost-Effectiveness Studies*. No. 0132. Bureau of Economic Analysis, 2024.

Frankovic, Ivan, Michael Kuhn, and Stefan Wrzaczek. "Medical innovation and its diffusion: Implications for economic performance and welfare." *Journal of macroeconomics* 66 (2020): 103262.

Frey, Bruno S. "How intrinsic motivation is crowded out and in." *Rationality and society* 6.3 (1994): 334-352.

Zweifel, Peter. "Innovation in health care through information technology (IT): The role of incentives." *Social Science & Medicine* 289 (2021): 114441.

Hofmann, Bjørn. "Internal barriers to efficiency: why disinvestments are so difficult. Identifying and addressing internal barriers to disinvestment of health technologies." *Health Economics, Policy and Law* 16.4 (2021): 473-488.

Greenhalgh, Trisha, et al. "Diffusion of innovations in service organizations: systematic review and recommendations." *The milbank quarterly* 82.4 (2004): 581-629.

Young, H. Peyton. "Innovation diffusion in heterogeneous populations: Contagion, social influence, and social learning." *American economic review* 99.5 (2009): 1899-1924.

Bass, Frank M. "A new product growth for model consumer durables." *Management science* 15.5 (1969): 215-227.

Easingwood, Christopher J., Vijay Mahajan, and Eitan Muller. "A nonuniform influence innovation diffusion model of new product acceptance." *Marketing Science* 2.3 (1983): 273-295.

Kanniainen, Juho, et al. "Forecasting the diffusion of innovation: A stochastic bass model with log-normal and mean-reverting error process." *IEEE Transactions on Engineering Management* 58.2 (2010): 228-249.

Jain, Dipak. "Marketing mix effects on the diffusion of innovations." *Working Paper, Northwestern University, Kellogg Graduate School of Management* (1992).

Bass, Frank M. "The relationship between diffusion rates, experience curves, and demand elasticities for consumer durable technological innovations." *Journal of business* (1980): S51-S67.

Dockner, Engelbert, and Steffen Jørgensen. "Optimal advertising policies for diffusion models of new product innovation in monopolistic situations." *Management science* 34.1 (1988): 119-130.

Jones, J. Morgan, and Christopher J. Ritz. "Incorporating distribution into new product diffusion models." *International Journal of Research in Marketing* 8.2 (1991): 91-112.

Kiesling, Elmar, et al. "Agent-based simulation of innovation diffusion: a review." *Central European Journal of Operations Research* 20 (2012): 183-230.

Decker, Reinhold, and Kumiko Gnibba-Yukawa. "Sales forecasting in high-technology markets: A utility-based approach." *Journal of product innovation management* 27.1 (2010): 115-129.

Katz, Michael L., and Carl Shapiro. "Technology adoption in the presence of network externalities." *Journal of political economy* 94.4 (1986): 822-841.

Escarce, Jose J. "Externalities in hospitals and physician adoption of a new surgical technology: an exploratory analysis." *Journal of health economics* 15.6 (1996): 715-734.

Iversen, Tor, and Ching-to Albert Ma. "Technology adoption by primary care physicians." *Health Economics* 31.3 (2022): 443-465.

Molitor, David. "The evolution of physician practice styles: evidence from cardiologist migration." *American Economic Journal: Economic Policy* 10.1 (2018): 326-356

Liu, Qiang, and Sachin Gupta. "A micro-level diffusion model for new drug adoption." *Journal of Product Innovation Management* 29.3 (2012): 372-384.

Barrenho, Eliana, et al. "Innovation diffusion and physician networks: Keyhole surgery for cancer in the English NHS." (2020).

Barrenho, Eliana, et al. "Innovation Diffusion Among Coworkers: Evidence from Senior Doctors." *Management Science* (2025).

Klausen, Liv Marit, Trond E. Olsen, and Alf Erling Risa. "Technological diffusion in primary health care." *Journal of health economics* 11.4 (1992): 439-452.

Doran, Tim, et al. "Pay-for-performance programs in family practices in the United Kingdom." *New England journal of medicine* 355.4 (2006): 375-384.

Scott, Anthony, et al. "The effects of an incentive program on quality of care in diabetes management." *Health economics* 18.9 (2009): 1091-1108.

Walker, Alex J., et al. "Variation in responsiveness to warranted behaviour change among NHS clinicians: novel implementation of change detection methods in longitudinal prescribing data." *bmj* 367 (2019).

Hamilton, Barton H., and Brian McManus. "Technology diffusion and market structure: Evidence from infertility treatment markets." *Available at SSRN 813826* (2005).

Abaluck, Jason, et al. *Fixing misallocation with guidelines: Awareness vs. adherence*. No. w27467. National Bureau of Economic Research, 2020.

Grol, Richard, et al. "Attributes of clinical guidelines that influence use of guidelines in general practice: observational study." *Bmj* 317.7162 (1998): 858-861.

Grol, Richard, and Jeremy Grimshaw. "From best evidence to best practice: effective implementation of change in patients' care." *The lancet* 362.9391 (2003): 1225-1230.

Wu, Bingxiao, and Guy David. "Information, relative skill, and technology abandonment." *Journal of Health Economics* 83 (2022): 102596.

Finkelstein, Amy, et al. "A taste of their own medicine: guideline adherence and access to expertise." *American Economic Review: Insights* 4.4 (2022): 507-526.

Forrest, Robin et al. "Preferences for speed of access versus certainty of the survival benefit of new cancer drugs: a discrete choice experiment." The Lancet Oncology 25.12 (2024): 1635 – 1643.

Grimm, Sabine E., John W. Stevens, and Simon Dixon. "Estimating future health technology diffusion using expert beliefs calibrated to an established diffusion model." *Value in Health* 21.8 (2018): 944-950.

Compagni, Amelia, Valentina Mele, and Davide Ravasi. "How early implementations influence later adoptions of innovation: Social positioning and skill reproduction in the diffusion of robotic surgery." *Academy of Management Journal* 58.1 (2015): 242-278.

Skinner, Jonathan, and Douglas Staiger. "Technology diffusion and productivity growth in health care." *Review of Economics and Statistics* 97.5 (2015): 951-964.

Greenhalgh, Trisha, et al. "Diffusion of innovations in service organizations: systematic review and recommendations." *The milbank quarterly* 82.4 (2004): 581-629.

Wang, Peng, et al. "Using social network analysis to identify influential community organizations." *Social Science & Medicine* 365 (2025): 117477.

Allcock, Jake Alan, et al. "Landscape of digital technologies used in the national health service in England: content analysis." *JMIR Formative Research* 8 (2024): e51859.

Kalyani, Aakash, et al. *The diffusion of new technologies*. No. inetwp222. Institute for New Economic Thinking, 2024.

Wilding, Anna, et al. "Geographic inequalities in need and provision of social prescribing link workers a retrospective study in primary care." *British Journal of General Practice* (2024).