SOCIOLOGY OF HEALTH & ILLNESS

*Sociology of Health & Illness Vol. xx No. xx 2020 ISSN 0141-9889, pp. 1–18*
doi: 10.1111/1467-9566.13147

# The diffusion of innovative diabetes technologies as a fundamental cause of social inequalities in health. The Nord-Trøndelag Health Study, Norway

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**Abstract** This study investigates patterns of adoption and diffusion of innovative health technologies by socioeconomic status (SES) in order to assess the extent to which these technologies may be a fundamental cause of health-related inequalities. Quantitative analyses examined SES-based inequalities in the adoption and diffusion of diabetes technologies. Diabetes data from three panels of the Nord-Trøndelag Health Study (HUNT), Norway, were combined with income and education data. Cross-sectional and longitudinal regression analyses were used to examine relevant inequalities. Cross-sectional analyses suggest often present SES-based gradients in the adoption of diabetes technologies, favouring high-SES groups. Statistically significant differences ($p \leq 0.05$) were most often present when technologies were new. In a cohort followed from 1984 to 1997, high SES individuals were more likely to adopt insulin injection technologies but, due to modest sample sizes, these inequalities were not statistically significant after adjusting for age, gender, and duration of illness. Moreover, compared to low SES individuals, high SES individuals are more active users of diabetes technologies. Results suggest that SES-based variations in access and use of innovative health technologies could act as a mechanism through which inequalities are reproduced. This study provides a discussion of mechanisms and a methodological foundation for further investigation.

**Keywords:** social inequality, health, diabetes, technology, innovation, HUNT

## Introduction

*Background and theory*

As public health becomes increasingly commodified, innovative technologies are an increasingly important resource through which treatment, care and promotion of human health is bought, sold and traded (Casper and Morrison 2010, Gabe and Monaghan 2013, Lupton 2015, Piot 2012). Market forces have been shown to strengthen the typical inverse relationship between the quality of medical care and need, where higher quality care is generally received by those in a position of least need (Hart 1971). This may be further strengthened by the legitimisation of medical technologies as a means of promoting a patient empowerment (i.e. individual responsibility) discourse in support of 'realising system objectives of increased efficiency and reduced expenditures' (Øversveen 2020, Weiss 2019). The importance of traditional forms of capital – such as economic, symbolic, social or cultural – on the ability to exploit advantages resulting from the adoption of innovative technologies provides a potential mechanism for the (re)production of imbalances in power, and therefore social inequalities (Gabe and Monaghan 2013, Grenfell 2014, Rogers 2003). There is increasing support for the argument that the power needed to attain access to, and proficiently exploit, modern medical technologies in a systemic environment increasingly pressured by economic incentives is dependent not just on individual purchasing power (i.e. economic capital), but on the resources and advantages afforded by high social status (i.e. cultural, social and symbolic forms of capital) (Øversveen 2020, Weiss 2019).

These concerns have become particularly relevant as technological advances in the health sector coincide with increasing inequalities in and around health (Beckfield *et al*. 2015, Mackenbach 2012, Marmot 2015). Efforts to reduce health inequalities have been disappointing, due partly to a relative lack of understanding of mechanisms and meta-mechanisms responsible for (re)producing inequalities (Freese and Lutfey 2011, Mackenbach 2012, Phelan and Link 2013). Link and Phelan's Fundamental Cause theory (FCT) offers a prominent explanation, positing that advantages associated with money, power, prestige, knowledge and social connections are deployed by individuals to avoid risk factors associated with illness or death (Phelan and Link 2013, Phelan *et al*. 2010). While various empirical studies of FCT have supported its various premises, many of the theory's tests have focused on the role of advantaged access to particular health technologies as a means of improving health status despite FCTs apparent inattention to established research in and around technology and innovation (Chang and Lauderdale 2009, Freese and Lutfey 2011, Link *et al*. 1998, Lutfey and Freese 2005, Masters *et al*. 2015, Phelan and Link 2013, Phelan *et al*. 2004). Other researchers have raised arguments in an attempt to further the theory's development in various directions (Clouston *et al*. 2016, Freese and Lutfey 2011, Lutfey and Freese 2005, Øversveen *et al*. 2017, Veenstra 2017), with some focusing on the theory's relationship with the relevant science of innovation and technology (Chang and Lauderdale 2009, Clouston *et al*. 2016, Weiss *et al*. 2018).

Further understanding the role that diffusion processes have on reproducing inequalities in accessing and exploiting technological innovations in health, may also provide a deeper understanding of the pathways through which fundamental causes of social inequalities manifest in the modern techno-society. To this end, recent research has applied a diffusion of innovations perspective to explore premises related to the FCT in more detail (Chang and Lauderdale 2009, Glied and Lleras-Muney 2008, Korda *et al*. 2011). Originally developed and elaborated on by Rogers, the diffusion of innovations theory maintains that novel ideas, practices or objects are adopted earliest by individuals of higher social position, whom thereafter accumulate advantage resulting from these innovations (Rogers 2003). In the case of health-related innovations – such as net-based applications, gene technology, or new treatment or diagnostic tools – this could mean a widening of social inequalities. However, the influence adoption of innovations in health has on changes in social inequalities may depend significantly on the type of health technology in question (Goldman and Lakdawalla 2005, Weiss *et al*. 2018). Research would seem to benefit from further exploring various types of technology used to prevent, diagnose, treat or manage illness using a single cohort over time. Furthermore, additional analyses are needed to test the validity of these relationships even in a context of strong welfare regimes using well-established single-payer universal healthcare systems.

*Aims*

This study investigates whether innovative health technologies, and associated improvements in disease management, diffuse unequally by socioeconomic status (SES), giving rise to inequalities that are stronger when technologies are new. In order to achieve this objective, this study's aims were threefold: (i) to measure the probability of adopting a new diabetes technology (i.e. diffusion patterns) based on education and income; (ii) to investigate use patterns of diabetes technologies based on education and income (the second aim differs from the first in that the latter is not just concerned with whether or not a technology is adopted, i.e. accessed for use, but instead to investigate the interaction between adopter and technology to identify variations in the ways in which the technology is used, i.e. by the user, to exploit its potential benefits) and; (iii) to investigate whether potential variations in SES-based adoption and diffusion have an effect on inequalities in relevant health outcomes.

*Diabetes as a case*

Diabetes is a major cause of morbidity and mortality, affecting a growing number of individuals internationally (including Norway, where rates have increased from 2.5% in 2004 to 3.5% in 2016) (Stene *et al.* 2017, World Health Organization 2016). Current international research has documented increased prevalence, poorer regulation and control, and increased mortality for low SES groups, even in nations with strong universal healthcare systems (Agardh *et al.* 2011, Grintsova *et al.* 2014, Ricci-Cabello *et al.* 2010, Scott *et al.* 2017, Stene *et al.* 2017). Furthermore, effective management and control of diabetes is very dependent on active self-management and the use of technologies (Franklin 2016, Lutfey and Freese 2005, Øversveen 2020, Ritholz *et al.* 2007, Scott *et al.* 2017). Although user perceptions of these technologies differ, research highlights that many of these technologies have documented improvements in outcomes for both type 1 and type 2 diabetes (Franklin 2016, Naranjo *et al.* 2016, Ritholz *et al.* 2007). For example the adoption of continuous glucose monitors and insulin pens have demonstrated substantial improvements in glycated haemoglobin (HbA1c) levels, a form of haemoglobin used to identify 90-day average plasma glucose, when compared with older technologies (Anderson and Redondo 2011, Asche *et al.* 2010, Ritholz *et al.* 2010). This is supported by the current research establishing a variation in HbA1c levels of 0.5 per cent as clinically significant (Lenters-Westra *et al.* 2014).

*Norwegian context*

Norwegian health care is characterized by a predominantly public funded universal system of coverage where only 15 per cent is funded through out-of-pocket payments (Ringard *et al.* 2014). Out of pocket fees are used on co-payments for general practitioner (GP) and specialist visits, dental care, and pharmaceuticals, but are generally fixed at the national level and often included in an annual out-of-pocket cap. Inpatient care at public hospitals in Norway is free (Vikum *et al.* 2013). The largely semi-decentralized structure of health care in Norway administers specialist services at the state level (since 2002) through four Regional Health Authorities and primary care services at the municipality level (Ringard *et al.* 2014). Since 2001, nearly all Norwegian citizens have been assigned to specific regular GPs, who act as gatekeepers for specialist and elective services (Vikum *et al.* 2013).

Recent reforms include efforts to decentralize services (first half of the study period), efforts to increase efficiency of service delivery, and structural transformations focused on both increasing coordination between service providers and increasing patient autonomy (second half of the study period) (Ringard *et al.* 2014). Wait times, however, remain relatively long, geographical variations (rural/urban) persist, and despite very low levels of inequality compared to other EU nations, social inequalities in health are an issue of concern (Ringard *et al.* 2014).

Diabetes specialists are ultimately responsible for prescribing the use of State-insurance-covered technologies. These decisions, however, are often made in collaboration with other health personnel close to the potential user (i.e. patient) as well as in discussion with the potential user. National guidelines exist for prescribing State-insurance-covered technological aids, however, are often used in practice as open recommendations that are interpreted and implemented based on conditions and priorities specific to the local institution of care (i.e. variation between hospitals and between regions), as well as conditions and characteristics specific to the potential user. Importantly, however, all these technologies are also available in some form on the private market and therefore can be bought and used by individuals with sufficient capital (financial, social, cultural), particularly when considering that not all parts of these technologies have always been covered by State insurance schemes.

## Methods

### *Data sources*

The Nord-Trøndelag Health Study (HUNT) is a county-level public health study started in 1984 with the objective of surveying and measuring the health of the entire county's adult population (≥20 years of age). The survey's database currently includes data from three cohort panels during 1984–1986 (HUNT 1, N = 77,212 or 89% of those invited), 1995–1997 (HUNT 2, N = 65,237, 69.5%), and 2006–2008 (HUNT 3, N = 50,807, 54.1%) (Krokstad *et al.* 2012). The total population of the county changed by less than three per cent over the 25-year span of the study, and the region is generally considered to be representative of the country as a whole (Krokstad *et al.* 2012, Vikum *et al.* 2013). The survey provides a total of 166,758 observations available from 97,251 individuals who have answered either one (n = 48,414), two (n = 28,167), or all three (n = 20,670) of the surveys (Vikum *et al.* 2013). For this study, survey data were merged with education and income data from the national registry, obtained via Statistics Norway (SSB).

### *Technologies*

All three HUNT surveys include an additional diabetes survey for those who report once or currently having diabetes on the general survey. Table 1 provides an overview of the variables included in this study from each HUNT survey.

The various technologies included in this study, and their approximate time of adoption, are presented in Figure 1. These technologies represent broad categories of diabetes technologies. Although other broad treatment methods for diabetes were available at the time of these surveys, they were either non-technology dependent (e.g. lifestyle changes) or marginal technologies with very few users (limiting potential analyses). Time of adoption for these technologies was estimated using relevant literature as well as historical reference via consultation with the Norwegian Diabetes Association (dating back to 1948) and reference to the 1988 Norwegian guidelines for diabetes treatment (Clarke and Foster 2012, Midthjell *et al.* 1988, Palanker *et al.* 2011, Selam 2010).

Table 1 *Variables used from the three cross-sectional surveys in the Nord-Trøndelag Health Study (HUNT), Norway. Dates for each HUNT survey represent start/end period for data collection*

| | |
|---|---|
| HUNT 1 (1984–1986) | Measuring urine sugar at home |
| | Measuring blood sugar at home |
| | Injection of insulin at home (using syringe) |
| HUNT 2 (1995–1997) | Measuring blood sugar at home using strips |
| | Measuring blood sugar at home using a digital device |
| | Injection of insulin at home using a syringe |
| | Injection of insulin at home using a pen |
| | Injection of insulin at home using a pump |
| | Frequency of blood glucose measurements (weekly) |
| HUNT 3 (2006–2008) | Measuring blood sugar at home (any method) |
| | Injection of insulin at home using a pen |
| | Injection of insulin at home using a pump |
| | Use of laser eye treatment |
| | Frequency of blood glucose measurements (weekly) |
| Across all HUNT surveys | Length of disease history |

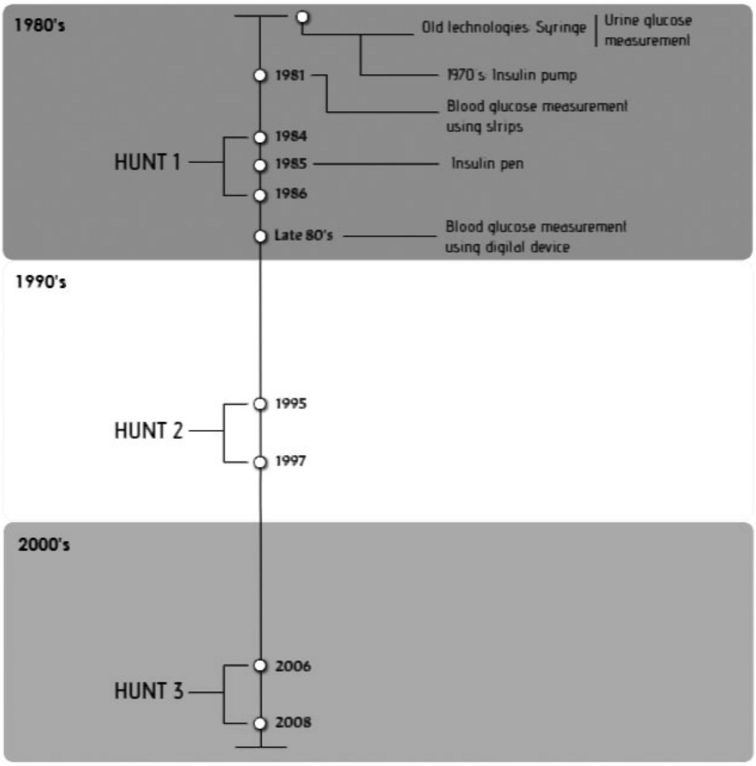


Figure 1 *Reported use of diabetes technologies by participants in the Nord-Trøndelag Health Survey (HUNT), Norway, and their approximate year of adoption in relation to start/end dates for data collection in each HUNT study*

*Socioeconomic status*
Socioeconomic status was measured using participant education and income. Pensionable income data as the sum of personal income for each year from 1984 to 2008 was used as this was the only income variable available for all years dating back to 1984. Respondents were then divided into high- and low-income groups based on average median yearly income. Education level has been recoded into three groupings, low (lower secondary schooling), medium (upper/post-secondary schooling), and high (university education), based on the National Standard Classification of Education in Norway (NUS) during the period 1984–2008.

*Diabetes sample and statistical analyses*
Our analyses include individuals who have reported currently or once having diabetes on any one of the HUNT 1 (n = 2248), HUNT 2 (n = 2028), and HUNT 3 (n = 2264) general surveys. Importantly, our analyses are not limited only to individuals with diabetes who have responded on *more than one* of these surveys, as this significantly limited sample sizes (HUNT 1 and 2 n = 524, HUNT 2 and 3 n = 569, HUNT 1–3 n = 137), however, our specific analyses are represented by this limitation (more on this below). Average age of those responding currently or once having diabetes is 69 years for HUNT 1 (SD = 14, min.–max. = 21–100), 66 years for HUNT 2 (SD = 14, min.–max. = 20–98), and 64 years for HUNT 3 (SD = 13, min.–max. = 20–94). Furthermore, of this sample, 44 per cent are male in HUNT 1, 48 per cent in HUNT 2, and 52 per cent in HUNT 3.

Individuals who have responded having diabetes on the general survey are then followed up using a diabetes-specific survey in each HUNT study (HUNT 1 n = 1758, HUNT 2 n = 1630, HUNT 3 n = 1824, HUNT 1 and 2 n = 347, HUNT 2 and 3 n = 387, HUNT 1–3 n = 86). Diabetes was, in part, well-suited for this analysis due to the advantage of similar diabetes surveys spanning all HUNT studies, allowing for relatively simple comparisons of most variables between cohorts. Some exemptions are worth noting, however. Number of years with diabetes diagnoses in the HUNT 1 sample was calculated using the equation *([birth year + age at time of survey completion] − year of diagnosis)*, whereas variables for number of years with diabetes diagnosis in HUNT 2 and HUNT 3 were previously available in the dataset. The two insulin pen types (disposable and standard) included in the HUNT 2 survey were merged into a single insulin pen variable to simplify comparison with the HUNT 3 survey (which does not distinguish between multiple pen types). Mean group HbA1c values, adjusted for age, were calculated for each SES and technology category (in HUNT 1, averages were calculated using non-fasting capillary glucose due to an absence of HbA1c values). In addition, due to survey question formulation, non-respondents (i.e. missing values) of questions regarding technology use were recoded as non-adopters (i.e. non-users), to differentiate from individuals who

Table 2 *New and old diabetes technologies in each Nord-Trøndelag Health Survey (HUNT), Norway*

| *Technology type* | *HUNT 1* | *HUNT 2* | *HUNT 3* |
|---|---|---|---|
| Measuring urine sugar at home | Old | – | – |
| Measuring blood sugar at home using strips | New | Old | Old |
| Measuring blood sugar at home using digital | – | New | Old |
| Injecting insulin at home using syringe | Old | Old | Old |
| Injecting insulin at home using pump | – | Old | Old |
| Injecting insulin at home using pen | – | New | Old |


Figure 2 *Age standardised* self-reported diabetes prevalence (%) by socioeconomic status in HUNT1–HUNT3. Nord-Trøndelag Health Survey (HUNT), Norway. *Directly standardised towards the total Norwegian population January 1st year 2000*

specifically responded using these technologies (i.e. adopters or users). In other words, all individuals who did not specifically report using included technologies were recoded as non-users.

Based on adoption dates and relevant treatment guidelines, Table 2 below presents technologies considered old and new in each HUNT survey:

Analyses include a cross-sectional linear regression plus post-estimation to calculate age-adjusted average HbA1c levels with 95 per cent confidence intervals (95% CI) for each HUNT cohort based on SES and technology type. Furthermore, logistic regression models yielding odds ratios (OR) with 95 per cent CI were specified to examine associations between SES and the use of new technology independently in each cohort (i.e. cross-sectional analyses of HUNT 1–3) as well as in a cohort of adopters versus non-adopters followed from HUNT 1 to HUNT 2 (HUNT 3 data are excluded from this latter analysis as it does not include technologies considered innovative, i.e. adoption after HUNT 2). All analyses were performed using Stata/SE 15.1 (StataCorp 2017).

## Results

### *Inequalities in diabetes prevalence and management*

Figure 2 presents age standardised diabetes prevalence rates in each HUNT study based on education and income. Across all HUNT surveys, the majority of individuals that reported currently or once having diabetes are from low SES groups. An educational gradient in prevalence persists across HUNT surveys. Also apparent is the steady increase in total prevalence over the entire study period (2.67%, 2.85% and 3.62% for each HUNT survey, respectively). Some socioeconomic groups, however, seem to disproportionately account for this total increase. When compared with other socioeconomic groups, medium educated and high-income groups account for a larger proportion of this increase over time.

Table 3 presents HbA1c levels for participants with diabetes in each HUNT survey based on SES and technology type, adjusted for age. The data suggest a general decline in average

Table 3 *Mean HbA1c levels by socioeconomic status and type of technology, with 95 per cent confidence intervals (95% CI) and adjusted for age. Nord-Trøndelag Health Study (HUNT), Norway*

| | *HUNT 1*[1] | | *HUNT 2*[2] | | *HUNT 3*[2] | |
|---|---|---|---|---|---|---|
| | *HbA1c* | *95% CI* | *HbA1c* | *95% CI* | *HbA1c* | *95% CI* |
| Education | | | | | | |
| Low | 8.40 | 8.19–8.63 | 8.20 | 8.08–8.32 | 7.21 | 7.08–7.34 |
| Medium | 8.85 | 8.51–9.20 | 8.05 | 7.91–8.18 | 7.27 | 7.18–7.37 |
| High | 7.91 | 7.01–8.83 | 8.00 | 7.71–8.29 | 7.14 | 6.97–7.32 |
| Income | | | | | | |
| Low | 8.47 | 8.28–8.66 | 8.14 | 8.04–8.24 | 7.18 | 7.06–7.29 |
| High | 9.16 | 8.28–10.04 | 8.06 | 7.84–8.28 | 7.27 | 7.18–7.36 |
| Glucose tech | | | | | | |
| Old | 9.14 | 8.85–9.43 | 8.41 | 8.07–8.74 | 7.33 | 7.25–7.41 |
| New | 9.75 | 9.28–10.22 | 8.48 | 8.35–8.60 | – | – |
| Insulin tech | | | | | | |
| Old | 10.10 | 9.65–10.55 | 9.23 | 8.87–9.59 | 7.98 | 7.85–8.11 |
| New | – | – | 8.92 | 8.74–9.09 | – | – |

[1]Non-fasting capillary glucose measurement used as fasting glycated haemoglobin (HbA1c) values unavailable.
[2]In HUNT 2 and 3 whole blood samples were used to collect fasting HbA1c levels.

glucose levels for all groups over time. Differences otherwise are mostly minor and scattered. The exception is in HUNT 1, where clinically significant (>0.5%) variations in HbA1c levels exist, appearing to favour individuals with high (university) education. In contrast, however, clinically significant variations seem to also favour low-income individuals and users of old glucose technology in HUNT 1.

*Inequalities in the use of diabetes technologies*

Table 4 illustrates that social inequalities in the use of diabetes technologies exist regardless of technology type or measure of SES and are particularly strong when technologies are new. In HUNT 1, results suggest that high SES groups are generally more likely to use diabetes technology regardless of the type or age of the technology, however, inequalities are strongest for the use of new glucose measurement technology (GMT). Compared with the least educated group, those with medium education had a 1.46 times higher odds of reporting use of this technology, whereas the odds for the highest educated group was 3.25 times higher. The high-income group had 2.68 times higher odds compared with the low-income group. Inequalities for old technologies appear to be statistically non-significant across HUNT 1 results except for the use of old insulin injection technology (IIT), where income inequalities present statistically significant results (OR = 2.26 [1.17–4.39]). Results from HUNT 2 appear to present similar results in that inequalities favouring high SES groups are stronger for new technologies. Educational inequalities in the use of diabetes technologies in HUNT 2 are statistically significant between low and high (but not statistically significant between low and medium) educated for new IIT (OR = 1.82 [1.12–2.94]) and also statistically significant between low and medium (but not statistically significant between low and high) educated for new GMT (OR = 1.77 [1.40–2.24]). Although, in contrast to HUNT 1, low SES groups appear to be generally more likely than high SES groups to use old diabetes technologies (the exception being the high educated group for old glucose technology), all other inequalities in HUNT 2 are statistically non-significant, including all results for income-related inequalities. In HUNT 3, general

Table 4 *Cross-sectional associations between education level and income and use of diabetes technology in the Nord-Trøndelag Health Studies (HUNT), Norway, with odds ratio (OR) and 95 per cent confidence interval (95% CI)*

| | *Old glucose technology* | | *New glucose technology* | | *Old insulin technology* | | *New insulin technology* | |
|---|---|---|---|---|---|---|---|---|
| | *OR* | *95% CI* | *OR* | *95% CI* | *OR* | *95% CI* | *OR* | *95% CI* |
| HUNT 1 | | | | | | | | |
| Education | | | | | | | | |
| Low | 1.00 | ref | 1.00 | ref | 1.00 | ref | – | – |
| Medium | 1.15 | (0.91–1.45) | 1.46[1] | (1.09–1.97) | 1.23 | (0.88–1.71) | – | – |
| High | 1.43 | (0.84–2.43) | 3.25[1] | (1.84–5.75) | 1.74 | (0.91–3.32) | – | – |
| Income | | | | | | | | |
| Low | 1.00 | ref | 1.00 | ref | 1.00 | ref | – | – |
| High | 0.72 | (0.42–1.25) | 2.68[1] | (1.50–4.79) | 2.26[1] | (1.17–4.39) | – | – |
| HUNT 2 | | | | | | | | |
| Education | | | | | | | | |
| Low | 1.00 | ref | 1.00 | ref | 1.00 | ref | 1.00 | ref |
| Medium | 0.71 | (0.44–1.15) | 1.77[1] | (1.40–2.24) | 0.96 | (0.56–1.65) | 1.30 | (0.97–1.75) |
| High | 1.29 | (0.61–2.75) | 1.51 | (0.98–2.31) | 0.76 | (0.26–2.19) | 1.82[1] | (1.12–2.94) |
| Income | | | | | | | | |
| Low | 1.00 | ref | 1.00 | ref | 1.00 | ref | 1.00 | ref |
| High | 0.78 | (0.38–1.60) | 1.15 | (0.82–1.62) | 0.56 | (0.22–1.41) | 0.90 | (0.61–1.35) |
| HUNT 3 | | | | | | | | |
| Education | | | | | | | | |
| Low | 1.00 | ref | – | – | 1.00 | ref | – | – |
| Medium | 1.10 | (0.84–1.44) | – | – | 1.16 | (0.86–1.55) | – | – |
| High | 1.18 | (0.77–1.78) | – | – | 1.45 | (0.97–2.16) | – | – |
| Income | | | | | | | | |
| Low | 1.00 | ref | – | – | 1.00 | ref | – | – |
| High | 1.17 | (0.87–1.58) | – | – | 0.89 | (0.66–1.19) | – | – |

Adjusted for age, gender and length of illness.
[1]Signifies statistical significance.

inequalities in the use of technologies in bivariate analyses, favouring high SES groups, seems to reappear in spite of these technologies being considered old and regardless of the type of technology (the only exception being inequalities between income groups for old insulin technologies, which suggests greater use by the low-income group). However, all these inequalities are statistically non-significant after controlling for age, gender and length of illness.

Results, in general suggest that, when compared to income, level of education seems to have a greater effect on the use of diabetes technologies. Educational gradients consistently appear across our results, generally favouring high educated groups, but are particularly influential when technologies are new. Although results for level of income appear to be considerable, particularly in HUNT 1, suggesting trends similar to those found for education, income gradients are generally less consistent and prove to be in general less influential.

In addition to the inequalities presented in Table 4, results suggest that the frequency of using diabetes technologies also varies by SES, particularly for education. Available data from HUNT 2 and HUNT 3 (not available in HUNT 1) suggest that higher SES groups measure blood glucose more regularly than low SES groups regardless of technology type, however, differences appear greater when innovative technologies are available. In HUNT 2, the low-education group on average measured blood glucose 4.3 times per week, the medium educated group 4.9 times per week, and the high-educated group 7.9 times per week, suggesting a strong educational gradient favouring those with higher education. These numbers were 3.9 and 6.7 for low and high-income groups respectively. In HUNT 3, however, the low-educated group on average measured blood glucose 5.1 times per week, the medium-educated group 4.8 times per week, and the high-educated group 5.6 times per week. These numbers were 5.3 and 4.7 for low- and high-income groups respectively.

*Inequalities in the diffusion of diabetes technologies*

The development of innovative technologies during the period HUNT 1 (1984–1986) to HUNT 2 (1995–1997) creates an opportunity for investigating socioeconomic inequalities in the diffusion of innovative technologies by following adoption patterns of a single cohort throughout this time period. Unfortunately, the relatively limited size of this cohort reporting the use of relevant technologies ($N \leq 190$) greatly restricted the power of our statistical analyses.

Bivariate analyses suggest that, during this period, the adoption of IIT was unequally distributed by SES, favouring individuals with high education and income. Here again we see an educational gradient, with the number of adopters increasing with education level. For GMT, bivariate analyses indicate that adoption is associated with higher income, but not education. As shown in Table 5, however, after controlling for age, gender, and duration of illness together in a longitudinal analysis, inequalities in adoption become statistically non-significant due to a low number or respondents.

Interestingly, however, we see much higher overall diffusion rates for GMT for both education and income (88.9% and 89.0% respectively) over IIT (64.7% for both income and education), suggesting the presence of mechanisms either promoting the diffusion of innovative GMT over this period, or acting as barriers to the diffusion of innovative IIT regardless of SES. Furthermore, average HbA1c levels in adopter (GMT = 9.1%, IIT = 9.0%), compared to non-adopter (GMT = 8.7%, IIT = 9.9%), groups seem to be unequally distributed (see Table S1). There is a clinically significant difference of nearly 1 per cent for IITs, favouring

Table 5 *Odds ratio (OR) and 95 per cent confidence interval (95% CI) for adopting new glucose and insulin technologies by level of education and income in the HUNT 1 (1984–1986)–HUNT 2 (1995–1997) cohort. Nord-Trøndelag Health Study, Norway*

| | *New glucose technology* | | *New insulin technology* | |
|---|---|---|---|---|
| | *OR* | *95% CI* | *OR* | *95% CI* |
| Education | | | | |
| Low | 1.00 | Ref. | 1.00 | Ref. |
| Medium | 1.53 | (0.52–4.50) | 1.11 | (0.42–2.91) |
| High | 0.80 | (0.21–3.02) | 4.02 | (0.92–17.50) |
| Income | | | | |
| Low | 1.00 | Ref. | 1.00 | Ref. |
| High | 1.23 | (0.21–7.19) | 1.47 | (0.44–4.93) |

*Note*: All values in the table are adjusted for age, gender and length of illness.

adopters of new technologies, but a reverse relationship for GMTs favouring non-adopters, although in this case not clinically significant.

## Discussion

Our results suggest an overall increase in the prevalence of diabetes over the study period, accompanied by an overall decrease in HbA1c levels, regardless of SES or technology used. Results suggest a more active engagement by high SES groups, who often used technologies at a higher rate and frequency, demonstrating statistically significant educational inequalities in the use of innovative technologies that were not present for old technologies. These findings support results from a recent qualitative investigation by Øversveen (2020) into a similar topic. The diffusion of IITs demonstrated a similar trend over time, with an educational gradient favouring high SES. Diffusion rates for GMTs by SES, however, were scattered and absent of any similar trend. This may correspond with overall diffusion of GMTs during the study period, which was much higher than for IITs. In any case, longitudinal analyses for SES-based rates of adoption presented statistically nonsignificant results after controlling for age, gender, and duration of illness.

### *Social inequalities in diabetes management: understanding divergence in the present population*

Our results, particularly for education, suggest that adoption and diffusion patterns witnessed in the cohorts from each HUNT survey independently as well as in the cohort followed over a 10-year period from HUNT 1 to HUNT 2 support the diffusion of innovations theory. SES-based inequalities in the adoption of innovative technologies included in this study appear to suggest that as education level increases so too do the odds and rates of adoption, particularly when technologies are new. Diffusion rates for IITs appear to support these results while diffusion rates for new GMTs seems to suggest less conclusive, somewhat contradictory results. However, overall adoption for this technology is much higher than overall adoption for IITs, suggesting that these GMTs have diffused more rapidly than insulin injection technologies and therefore achieved nearer to complete diffusion over the 10-year follow-up period. This may explain the absence of clear trends in the diffusion of GMTs. In any case, these results offer evidence in support of a typical diffusion of innovations pattern, with early adopter groups generally consisting of individuals of higher SES and later adopters generally of lower SES (Rogers 2003).

The larger inequalities witnessed in the adoption and diffusion of innovative diabetes technologies is possibly due to higher SES patients more often using specialist services and/or being recommended for intense treatment regimens. Previous research has shown that clinicians often consider high SES patients to be more motivated and more capable of effectively utilising more intense treatment regimens that utilise innovative technologies (Lutfey and Freese 2005, Naranjo *et al*. 2016, Scott *et al*. 2017). This type of institutional agency, where treatment recommendations vary between high and low SES patients based on assessed capabilities, may result in these technologies being prescribed and recommended more often to higher SES patients (Brown *et al*. 2004, Lutfey and Freese 2005, Naranjo *et al*. 2016, Ricci-Cabello *et al*. 2010). Our results suggest that this effect may persist to a degree even in single-payer universal healthcare systems.

Although the institutional agency argument may offer an explanation for the unequal diffusion of technologies between high and low educated user groups, it does not offer a reasonable explanation for the higher total diffusion rates of GMT compared to IIT. Goldman and

Lakdawalla (2005) have previously concluded that innovations that simplify treatment and care act to reduce health disparities and it is possible that the innovation in glucose measurement simplifies diabetes treatment more so than the innovation in insulin injection. An alternative explanation, however, may lie in manufacturers of glucose measurement devices being sometimes willing to sell these devices at very low cost (or even free of charge), in the hope that patients will then continue to pay for the costly strips needed to use the devices (Clarke and Foster 2012, Lutfey and Freese 2005). State-led directives may reinforce this high rate of diffusion as the cost of obtaining and using digital glucose measurement devices were, during this period, covered by state insurance programmes (Midthjell *et al*. 1988). However, although patients were able to receive their first insulin pen free of charge from producers, state insurance programmes at the time did not cover the costs of continued use (Midthjell *et al*. 1988).

In any case, total diffusion rates may mask inequalities in use patterns (such as frequency), as demonstrated by high-educated patients in HUNT 2 on average measuring blood glucose nearly twice as often per week as low educated patients. This suggests that patients of lower SES may have received and used these devices for a period of time, but to a greater degree discontinued or reduced usage of the device, a finding supported by earlier research identifying relevant psychological and economic barriers (Lutfey and Freese 2005, Naranjo *et al*. 2016) and also further supported by the diffusion of innovations theory (Rogers 2003).

Although our results demonstrate that high SES groups are in some cases significantly more likely than low SES groups to use innovative technologies, it is less clear that these technological innovations are effectively used to improve disease management. If one accepts variance in HbA1c levels of 0.5 per cent as clinically significant, average HbA1c levels in this study do not show a clear advantage in favour of high SES groups or users of innovative technologies (Lenters-Westra *et al*. 2014).

*The (re)production of social inequalities in health: innovative technologies as a material and symbolic resource*

While our results do not offer conclusive evidence for causally explaining inequalities in health outcomes as a consequence of the unequal adoption and diffusion of medical technology, they do support the premise that innovative technology may be an important mechanism through which inequalities are (re)produced. The early adoption of health innovations may afford users with specific benefits, that can accumulate over extended periods, but which do not necessarily present as traditional markers of illness (Chang and Lauderdale 2009, Link *et al*. 1998, Rogers 2003). An innovative insulin pen, for example does not necessarily need to exhibit a significant impact on HbA1c levels for it to be a symbolic representation of the ideal patient or ideal user, which in the eyes of a clinician or other health-related personnel embodies a more worthwhile investment in additional resource allocation (Brown *et al*. 2004, Lutfey and Freese 2005, Naranjo *et al*. 2016). The clinician, in this case, is not just a gatekeeper to additional services, but also an agent of change, facilitating the flow of innovative technologies to users and providing a link between clients and a resource system (Rogers 2003).

Prior research has established that these ‘change agents’ communicate best and most often with individuals of similar (i.e. high) SES (Rogers 2003), a finding supported by the current research suggesting that high SES patients often accrue additional advantage from improved relationships with providers of care (Brown *et al*. 2004, Lutfey and Freese 2005). Likewise, evidence suggests that technological innovations symbolise a certain level of resource procurement in society that can then be exploited to a larger degree by individuals of high SES, reinforcing class distinctions and therefore a reproduction in inequalities in class-based power (Gabe and Monaghan 2013, Grenfell 2014, Veenstra 2017). In short, patients who master technological resources (regardless of the specific technology's effect on managing a particular illness) are often rewarded with an increased share of relevant valuable resources, further reinforcing the positive distinguishment of proficient users over less-proficient or non-users (Øversveen 2020). Furthermore, these subtle forms of symbolic inequalities fail to account for tangible inequalities in relevant quality of life associated with the proficient adoption and use of modern technologies, which are often designed to not just improve the effectiveness of managing illness but also reduce the suffering, discomfort or burden often associated with managing an illness (Lupton 2012). The high SES user, for example with the competence, knowledge, time and financial resources to ensure acquisition, and effective use, of a state-of-the-art GMT hooked up to a modern insulin pump, delivering real-time data to a computer-based analysis software program, is not only going to be afforded with a less intrusive and more stable and predictable quality of life, when compared with a low SES patient who is only able to, based on available capital (in all its forms), acquire rudimentary syringes and a basic digital glucose monitor for managing their diabetes. This actively engaged, high SES patient is also likely to, for reasons associated with their display of masterfully managing both their illness and the innovative technologies largely symbolising representations of modern medicine (i.e. the ideal 'empowered' patient), be 'rewarded' (albeit largely unconsciously, as a result of both internal and external cultural and systemic pressures) with higher quality clinical interactions and a greater level of effective institutional resource allocation (Øversveen 2020).

As our results therefore suggest, a diffusion of innovations perspective focused solely on rates of adoption and diffusion has the potential to conceal SES-based inequalities in the various ways in which these technologies are used, both consciously and unconsciously, to accrue advantages by individuals at various levels of the social strata. The potential symbolic (i.e. hidden representational) value of technological innovations in health combined with durable inequalities in the adoption, diffusion and individual exploitation (i.e. use) of these resources, offers an argument for these technological innovations as a potential mechanism for (re)asserting or maintaining status-based positions of power and naturally (re)producing fundamental inequality. However, it is clear that more research is needed to further investigate the relevance and strength of these relationships and it is our hope that the preliminary work in this paper can contribute to further exploring both theoretical and empirical developments.

### *Strengths and limitations*

The main strength of the current analysis is its presentation of a preliminary model for further investigation of the role technological innovations in health play in the persistence of health-related social inequalities. In so doing, this study also offers novel insights into the various mechanisms linking technological innovations with social inequalities in health, using diabetes as a case.

However, relevant limitations in this analysis include a comparatively small sample size, resulting in low statistical power in the longitudinal analyses, relatively coarse groupings for SES, and an inability to run analyses differentiating between type 1 and type 2 diabetes (type 1 is, for example, much more dependent on the use of technology, however, is much less common in the sample, so much so that the total number of individuals with type 1 diabetes alone is far too small for powering statistical analyses). Furthermore, mechanisms in selection processes may influence treatment options, where patients with more severe diabetes receive earlier recommendations for new technologies regardless of SES. Lower SES individuals, often suffering from more severe diabetes, also tend to be underrepresented in the survey material (Langhammer *et al*. 2012). Moreover, the current dataset did not allow for separating between non-adopters who would benefit from technological aids (of interest in this study) and non-adopters who do not have a need for technological aids (of little relevance for this study), therefore non-adopter (or non-user) categories likely include an artificially high representation of high-SES individuals (who are able to control often less severe forms of diabetes with lifestyle changes). Furthermore, due to our study using market availability as a way of determining the effective age of technologies, some devices that had been available for some time, but were particularly advanced (such as insulin pumps) have been categorised, alongside less advanced devices (such as syringe), as old technologies. Therefore, future studies may consider, instead, using total diffusion rates to determine the effective age of technologies (i.e. high diffusion rate = 'old' technology; low diffusion rate = 'new' technology), although this method does present its own challenges. As a result of the above limitations, it is important to note that SES-based inequalities in this study are likely to be under, rather than over, estimated.

Of further significance is a lack of information on the adoption of specific innovations within technological categories over time. Although types of technologies in our analysis are in some cases considered old technologies, new types of technologies are constantly being developed within these overarching categories that create a possibility for multiple adopter groups within the same technology type (e.g. 'old-style' vs. 'new-style' insulin pumps). Similarly, the specific technologies analysed in this study are all relatively old, even if modern devices exist within the general technological categories addressed in this study. Furthermore, the current dataset, unfortunately, did not allow consideration for variations in the duration of technology use. In some cases, reported users may have only used these technologies for short periods or discontinued use altogether.

The importance of this study, however, lies in its ability to use relatively old technologies (that have had time to diffuse) as a case for understanding adoption and diffusion patterns as they relate to SES-based inequalities, contributing to an understanding of the ways in which current and future innovative technologies are potentially following similar, not yet recognisable, patterns. Furthermore, the preliminary analytical model used in this study offers an important methodological first step for conducting similar analyses on contemporary technologies. Many of the limitations in this study, however, could be accounted for with the use of a more suitable dataset, which we are currently unaware exists.

## Conclusion

Although clear limitations exist in our study, and we consider much of this study to be preliminary and experimental in nature, our results suggest that SES-based variations in access and use of innovative technologies in health may act as a mechanism through which inequalities are reproduced, even in a country with tax-financed public health services with universal coverage. Our findings suggest that high SES groups tend to be earlier adopters, and more active users, of technological innovations in health. Furthermore, results from this study indicate that the rate of diffusion of these innovations influences the persistence of inequalities and has the potential to conceal SES-based variations in the use of these technologies. Evidence for a direct relationship between these inequalities and inequalities in diabetes-related health outcomes such as HbA1c levels is, however, somewhat surprisingly weak. Our data, however, does not address other important health-related outcomes, such as reductions in pain or stress, subjective improvements in effective use of time, or a simplified daily disease-management regimen associated with the use of new technology.

Although we would expect to see larger effects of SES-based inequalities in access and use of health improving technologies in countries with weaker welfare state regimes, future analyses would need to include cross-country comparisons, as well as address limitations associated with selection and analysis processes, to investigate whether this is true. Our results, however, suggest that although it is possible that income-based inequalities are moderated by strong welfare programmes, other significant SES-based inequalities in the access and use of health technologies, such as education-based inequalities, can persist even in a single payer system where these technologies are fully or partially covered by state-sponsored insurance programmes.

We argue that these inequalities may be partially explained by the ability of innovative technologies in health to act as a form of symbolic capital that reinforces the social hierarchy, therefore offering greater benefits to high SES groups who are in a better position to access and exploit additional resources used to promote health or manage illness. Innovative technologies in health may therefore be a resource allowing for the expression of the relative value of higher social position. This study will hopefully inform similar future analyses, which are necessary to provide further investigation into relevant, and important, social mechanisms that may provide insight into the persistence of growing social inequalities, including those in health.

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## Acknowledgements

The authors acknowledge the Heal-Tech project, which this work is a part of, and which has been central in the development of the ideas that this work is founded on. In addition, we thank Terje Andreas Eikemo, professor of Sociology at the Norwegian University of Science and Technology and Heal-Tech project lead as well as professor Kristian Midthjell of the HUNT research centre, the Norwegian Diabetes Association, and members of the CHAIN research centre for their advisory support.

## Author Contribution

**Daniel Weiss:** Conceptualization (lead); data curation (equal); formal analysis (equal); investigation (lead); methodology (equal); writing-original draft (lead); writing-review & editing (lead). **Erik R. Sund:** Conceptualization (supporting); data curation (equal); formal analysis (equal); investigation (supporting); methodology (equal); supervision (supporting); writing-original draft (supporting); writing-review & editing (supporting). **Jeremy Freese:** Conceptualization (supporting); formal analysis (equal); investigation (supporting); methodology (equal); supervision (supporting); writing-original draft (supporting); writing-review & editing (supporting). **Steinar Krokstad:** Conceptualization (supporting); data curation (equal); formal analysis (equal); funding acquisition (lead); investigation (supporting); methodology (equal); project administration (lead); resources (lead); supervision (lead); writing-original draft (supporting); writing-review & editing (supporting).

## Conflict of interest

None declared.

## Supporting information

Additional Supporting Information may be found in the online version of this article:

**Table S1.** Unadjusted values for number of adopters/non-adopters of diabetes technologies by socioeconomic status, with corresponding mean HbA1c values, for the cohort from HUNT 1 (1984–1986)–HUNT 2 (1995–1997) in the Nord-Trøndelag Health Study (HUNT), Norway.

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