

Implementation and evaluation of two nudges in an electronic prescribing system to optimise cost-effective prescribing in the hospital

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Abstract

Providing healthcare workers with cost information about the medications they prescribe can influence their decisions, particularly when that information is provided at the very moment they are faced with a prescribing decision. The current study aimed to analyse the impact of nudges that presented cost information to prescribers through an organisation's electronic prescribing system. The nudges were co-created by the research team composed of behavioural scientists and the lead hospital pharmacist. One nudge provided simple cost information (percentage difference between two brands of Mesalazine – Asacol and Octasa). The second nudge provided the potential annual cost-saving that could result if the cheaper medication was selected across the organisation. While the statistical analyses revealed that these nudges were not effective, administrative barriers were overcome, which may inform future research. For example, presenting aggregated cost information to the prescribers is possible even when the actual cost of medicine is confidential and cannot be displayed. Future research could reveal more behavioural factors that facilitate medication optimisation.

Keywords: behaviour change technique, nudge, prescription optimisation, prescribing behaviour

Introduction

Over the past decade, medication prescribing costs have risen annually in the National Health Service (NHS) in England. During 2019/20, the cost of medications – at list price – in hospital accounted for 55.9 per cent (£11.7 billion) of the total cost of medications used in the NHS, up from 53.9. per cent (£10.2 billion) in 2018/19 [1]. In 2019/20, the total hospital cost - at list price - increased by 14.0 percent on the previous year compared to an increase of just 5.2 percent in primary care [1]. Unless novel interventions occur, hospital expenditure on medicines is likely to continue increasing [2]. Where possible, promoting the use of a generic or cheaper brand of medicines may help reduce the increasing costs.

Findings from a systematic review suggest that cost awareness influences healthcare professionals' decision-making [3]. Based on this insight, Forgarty and colleagues created a nudge intervention to increase costs awareness at the very moment clinicians ordered a diagnostic test[4]. Their nudge was a message displayed on a blood CRP assays order form, which stated not only the individual cost of a single assay (1 GBP) but also the annual hospital expenditure in the previous year (200,914 GBPs). The researchers then compared the number of times the test was ordered in the 52 weeks before and after the nudge was applied and found a significant decrease in test orders. While not explicitly tested in Forgarty's study, the effectiveness of their nudge may partly be explained by the dual-process theories [5]. Dual-process theories suggest that two distinct cognitive systems influence behaviour. The reflective system is more effortful and allows for deeper analyses. The automatic system is typically faster and applies mental shortcuts. While all clinicians know that each test costs something (a rational system), they are unlikely to realise the unacceptably high aggregated costs looming if everyone orders those tests without good reason. Presenting clinicians with the high aggregated costs likely triggers clinicians' automatic systems and their corresponding response: more restrained use of low-cost tests. The current teams' intervention was planned based on the same insights and dual-process theories.

In the current study, two nudge interventions were designed to optimise prescribing of Mesalazine at a hospital trust in England. At the time of the study, Mesalazine was being sold as a more expensive medication, Asacol® and as a cheaper medication, Octasa®. Both were licensed to treat mild to moderate ulcerative Colitis and to maintain remission in

ulcerative Colitis. Across England's National Health Service (NHS) system, the costs of medicines are individually negotiated by NHS hospital trusts. The current NHS hospital trust had an active policy that entailed the cost of medicines that could not be presented directly to the clinicians. Consequently, the research team negotiated a way to present cost information that would not reveal those negotiated costs. After the nudges were agreed two study objectives were established. The first objective was to assess whether clinicians chose the cheaper brand when presented with simple cost information (percentage difference). The second objective was to assess whether clinicians chose the more affordable brand when presented with aggregated cost information (cost-saving to NHS system).

Methods

Study design

A cross-sectional study was conducted to evaluate the effectiveness of two nudges to optimise cost-effective prescribing at the Queen Elizabeth II Hospital, Birmingham, United Kingdom. The hospital has 1,215 patient beds, including 100 critical care beds [6]. Birmingham is the second-largest city in the United Kingdom and the 7th most deprived local authority out of England's 317 authorities [7].

Context

The hospital uses an electronic prescribing system called the Prescribing Information and Communication System (PICS). PICS supports full e-prescribing and drug administration, requesting and reporting of laboratory investigations, and clinical observations and assessments. It also allows for extensive order communications, including imaging requests and internal referrals[8]. During our study, each of the two electronic nudges was active for six months. The clinicians saw the nudges while they were in the process of prescribing either medication in outpatient and in-patient situations.

Intervention and implementation

The two nudges were co-created by the research team (composed of behavioural scientists) and the lead hospital pharmacist. One nudge provided simple cost information, i.e., the percentage difference between two alternatives. The second nudge presented aggregated cost information, i.e., the potential cost-saving attributed to the medicine switch nationally. Both messages are displayed in Figure 1.

Figure 1. The cost information used as the nudges to promote cost effective prescribing

Phase One (Oct 2020)

“For a newly initiated patients please use Mesalazine (Octasa), which is 50% of the cost. If continuation of treatment please use patient’s own medications and complete prescription as usual.”

Phase two (April 2021)

“Switch from Asacol to Octasa would save the health economy approx. £30million per year”

The nudges were implemented through PICS. The prescribing medicine on PICS involves clinicians inputting the relevant patient condition, Ulcerative Colitis. Several approved medication options will appear, and the clinicians can select the appropriate medicine. Prior to our intervention, the clinicians could directly select Asacol. During our intervention, when clinicians attempted to select Asacol, they then saw one of our nudges and a prompt that needed to be overridden (tick a box) to proceed with prescribing Asacol, see Figure 2.

Figure 2. Nudge presented in the PICS prescribing system

The screenshot shows a dialog box titled "Select Alternate Drug". Inside, "Mesalazine (Octasa)" is selected and highlighted in blue. Below the list, there are three buttons: "Continue", "Continue with Mesalazine (Asacol) prescription", and "Tick off All". At the bottom, there is a checkbox labeled "For newly initiated patients please use Mesalazine(Octasa), which is 50% of the cost. If continuation of treatment please use patient's own medications and complete prescriptions as usual.".

Outcomes and measurements

The following outcome measures were obtained from the hospital records: i) the total number of prescriptions of Asacol per day for 12 months prior to Intervention 1, 6 months during Intervention 1 and 6 months during Intervention 2, and ii) the total number of prescriptions of Octasa per day for 12 months prior to Intervention 1, 6 months during Intervention 1 and 6 months during Intervention 2.

Statistical analysis

A casual impact analysis was conducted over R-studio Version 1.4.1717. The analyses included data for the months indicated above for each nudge [9]. The casual impact analyses is an approach to estimating the causal effect of a designed intervention on a time series. Given a response time series (e.g., prescriptions of particular medicine after implementation of intervention) and a set of control time series (e.g., baseline prescription data), the package constructs a Bayesian structural time-series model. This model is then used to try and predict the counterfactual, i.e., how the response metric would have evolved after the intervention if the intervention had never occurred [10].

Results

Usage of Asacol

Simple Cost Nudge

As presented in Table 2 below, during the post-intervention period, the average number of Asacol prescriptions per day was 0.77. In the absence of an intervention, we expected an average of 0.60 with 95% [CI: 0.36, 0.86]. Subtracting the prediction from the observed response yields an estimate of the causal effect of the intervention on prescriptions of Asacol at 0.17 with 95% [CI -0.084, 0.41]. Post-intervention Asacol was 140.00 prescriptions compared to the predicted 108.65 prescriptions at baseline 95% [CI: 65.22, 154.23].

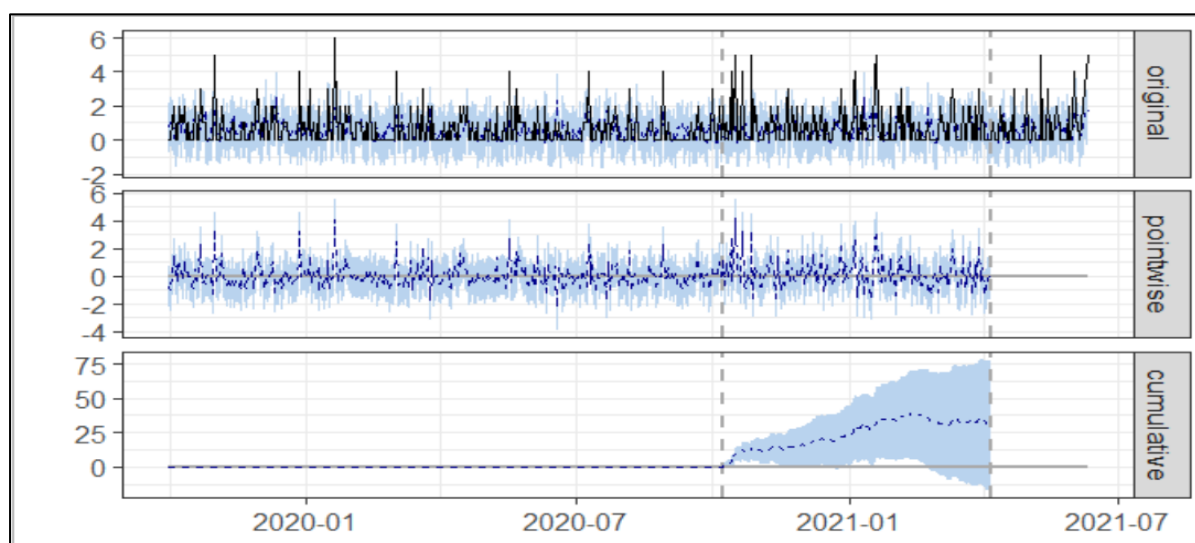
Table 1. Summary statistics - Causal Impact Analysis (pre-intervention 1 vs intervention 1) for Asacol

	Average no of prescription (Asacol)	Cumulative no of prescription (Asacol)
Actual	0.77	140.00
Prediction (SD)	0.6 (0.13)	108.6 (23.19)
95% CI	[0.34, 0.85]	[62.22, 154.23]
Absolute effect (SD)	0.17 (0.13)	31.35 (23.19)
95% CI	[-0.079, 0.43]	[-14.228, 77.78]
Relative effect (SD)	29% (21%)	29% (21%)
95% CI	[-13%, 72%]	[-13%, 72%]

Posterior tail-area probability p : 0.096, Posterior prob. of a causal effect: 90%

By contrast, in terms of the relative effect the prescription of Asacol showed an increase of +29% over a 95% confidence interval [-14%, +69%]. This indicates that, although the intervention appears to have increased the prescription in absolute terms, this effect is not statistically significant when considered in the context of the entire post-intervention period.

Figure 3. Trend of prescription of Asacol prior to and during the implementation of Intervention 1



Aggregated Cost Nudge

As presented in Table 3 below, during the post-intervention 2 period, the average number of Asacol prescription was 0.80. In the absence of an intervention 2, we would have expected an average of 0.67 with 95% [CI:0.36, 1.00].

Table 2. Summary statistics - Causal Impact Analysis (post- intervention 1 vs post intervention 2) for Asacol

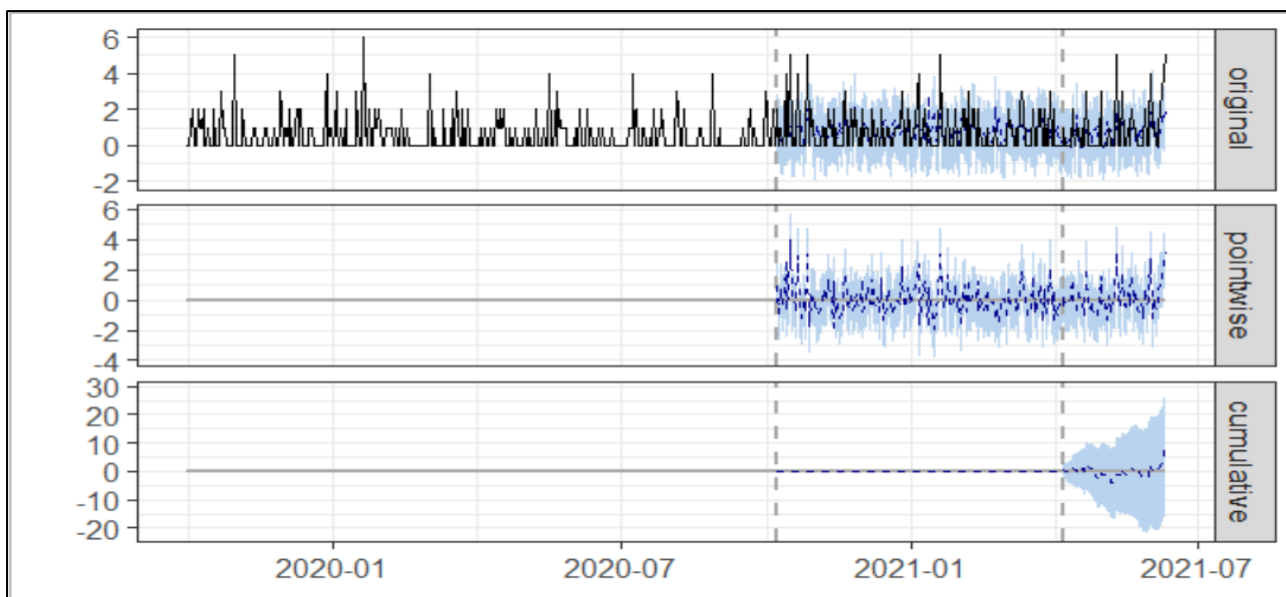
	Average no of prescription (Asacol)	Cumulative number of prescription (Asacol)
Actual	0.8	52.0
Prediction (SD)	0.67 (0.17)	43.28 (10.89)
95% CI	[0.36, 1]	[23.21, 64.86]
Absolute effect (SD)	0.13 (0.17)	8.72 (10.89)
95% CI	[-0.2, 0.44]	[-12.9, 28.79]
Relative effect (SD)	20% (25%)	20% (25%)
95% CI	[-30%, 67%]	[-30%, 67%]

Posterior tail-area probability p: 0.221, Posterior prob. of a causal effect: 78%

In absolute terms, subtracting the prediction from observed responses yields the estimate of the causal effect of our intervention to improve Asacol prescribing. Table 3 shows this effect is 0.13 with a 95% [CI:-0.20, 0.44]. Sum of individual data points during the post-intervention period indicates overall number of prescriptions was 52.00. In the absence of intervention the expected sum is 43.28 with 95% [CI: 23.21, 64.86].

In relative terms, the prescription of Asacol showed an increase of +20% with 95% [CI:-30%, +67%]. This suggests that although the intervention appears to have caused a positive effect, the effect is statistically not significant in relation to the entire post-intervention period. The probability of obtaining this effect by chance is $p = 0.22$. This means the effect may be spurious and would generally not be considered statistically significant.

Figure 4. Trend of prescription of Asacol post intervention 1 and post intervention 2



Octasa usage

Simple Cost Nudge

During the post-intervention period, the average number of Octasa prescribed per day was 3.22. In the absence of an intervention, we would have expected an average response of 3.40 with 95% [CI:2.94, 3.91]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the prescription of Octasa. This effect is -0.18 with a 95% [CI:-0.69, 0.27]. Summing up the individual data points during the post-intervention period (which can only sometimes be meaningfully interpreted), the total Octasa usage was 582 prescriptions. Had the intervention not taken place, we would have expected 614.60 prescriptions. The 95% interval of this prediction is [532.48, 706.87]. In relative terms, the Octasa prescription showed a decrease of -5.3% with 95% [CI:-20%, +8%]. This was a statistically insignificant result. The apparent effect could be the result of random fluctuations that are unrelated to the intervention. The probability of obtaining this effect by chance is $p = 0.231$. This means the effect may be spurious and would generally not be considered statistically significant.

Table 3. Summary statistics - Causal Impact Analysis (pre- intervention 1 vs intervention 1) for Octasa

	Average no of prescription (Octasa)	Cumulative no of prescription (Octasa)
Actual	3.22	582.0
Prediction (SD)	3.40 (0.24)	614.6 (43.86)
95% CI	[2.9, 3.9]	[532.5, 706.9]
Absolute effect (SD)	-0.18 (0.24)	-32.60 (43.86)
95% CI	[-0.69, 0.27]	[-124.87, 49.52]
Relative effect (SD)	-5.3% (7.1%)	-5.3% (7.1%)
95% CI	[-20%, 8.1%]	[-20%, 8.1%]

Posterior tail-area probability p : 0.231, Posterior prob. of a causal effect: 77%

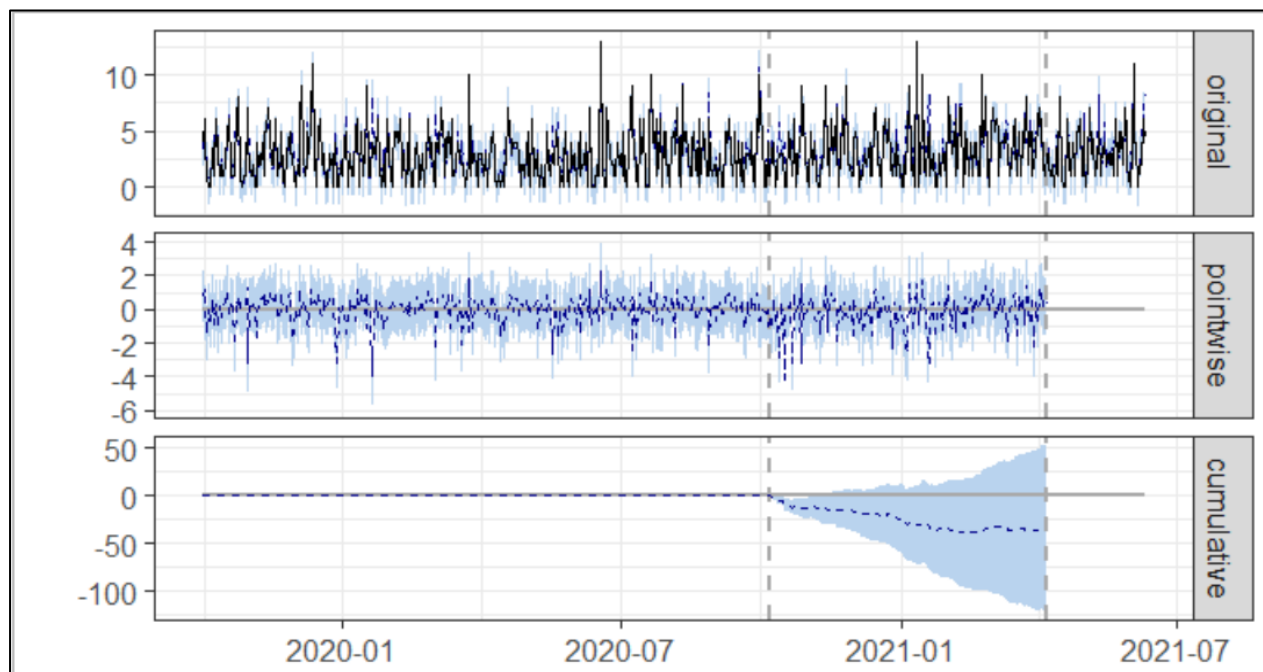


Figure 5. Trend of prescription of Octasa prior to and during the implementation of Intervention 1

Aggregated Cost Nudge

During the post-intervention period, the average number of Octasa prescribed per day was 3.1. In the absence of an intervention, we would have expected an average response of 3.30 with 95% [CI: 2.94, 3.91]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the prescription of Octasa. This effect is

-0.23 with a 95% interval of [-0.69, 0.22]. Further information is available in Table 5 and its illustrated in Figure 6.

Table 4. Summary statistics - Causal Impact Analysis (post- intervention 1 vs post intervention 2) for Octasa

	Average no of prescription (Octasa)	Cumulative no of prescription (Octasa)
Actual	3.1	200.0
Prediction (SD)	3.3 (0.24)	215.0 (15.70)
95% CI	[2.8, 3.8]	[183.8, 245.5]
Absolute effect (SD)	-0.23 (0.24)	-14.96 (15.62)
95% CI	[-0.69, 0.22]	[-45.08, 14.00]
Relative effect (SD)	-7 % (7.3%)	-7% (7.3%)
95% CI	[-21%, 6.5%]	[-21%, 6.5%]

Posterior tail-area probability p: 0.162, Posterior prob. of a causal effect: 84%

Summing up the individual data points during the post-intervention period (which can only sometimes be meaningfully interpreted), the total Octasa usage was 200 prescriptions. Had the intervention not taken place, we would have expected a sum of 215. The 95% interval of this prediction is [183.8, 245.5]. The above results are given in terms of absolute numbers. In relative terms, the response variable showed a decrease of -7%. The 95% interval of this percentage is [-21%, +6.5%]. This means that, although it may look as though the intervention has exerted a negative effect on the prescription of Octasa when considering the intervention period as a whole, this effect is not statistically significant, and so cannot be meaningfully interpreted.

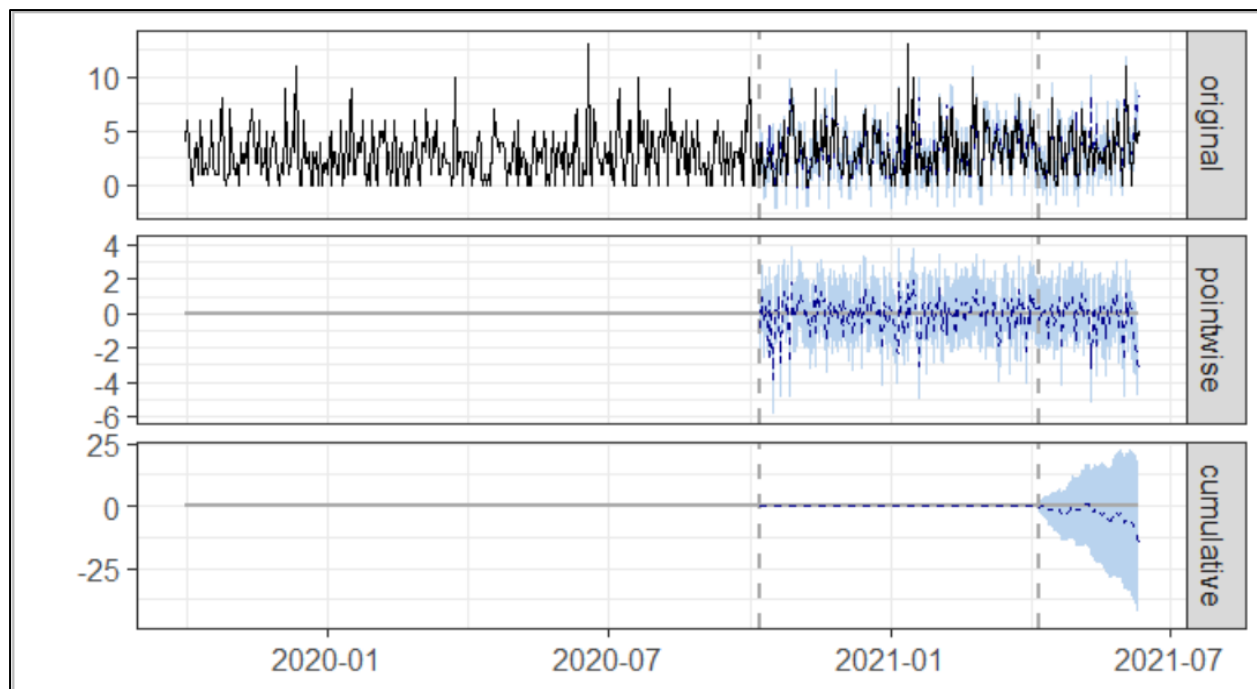


Figure 6. Trend of prescription of Octasa post intervention 1 and post intervention 2

Discussion

The current paper evaluated the impact of two nudges. The nudges were implemented through an electronic prescribing system already in use at the hospital. Both nudges aimed to increase clinicians' prescriptions of Octasa relative to Asacol. The first used simple cost information (percentage difference) and the second used aggregated cost information (potential saving for the NHS system). Our results suggest that neither nudge was effective.

Nudges do not always work. A recent systematic review of 15 studies, evaluating 20 different interventions studies found that 20% of the intervention did not work [11]. Nudges are designed to non-coercively influence behaviour without forbidding options [12-15], and it is the clinicians who must interpret and act. If clinicians do not trust the message, delivered in the electronic prescribing system (or its assumed messenger), they may purposely choose to go against it. Such behaviour may be attributed to a host of findings by behavioural science and psychology literature. For instance, prescribers may have experienced alert fatigue, essentially checking the tick-box to move on before reading the message [16]. Alternatively, reactance theory suggests that, whilst in several situations a person does not realise they are being nudged [17], there may be a reactive response that involves a sense of loss of freedom to prescribe as they judge necessary.[18]. A third

possibility is that prescribers who read the messages did not understand them, as our use of aggregated costs likely made the messages more obscure. Thus, a central lesson learnt from the current intervention is that prescribers may experience behavioural inconsistency and fatigue. This is largely an automatic response that can dampen the power of nudges to influence prescribing behaviour and decisions, in both secondary and primary care.

One of the major strengths of this study is that there are ways to present cost information even when cost information is confidential. We presented the cost in terms of percentile difference and in terms of aggregated cost-savings attributed to the health system. Of course, different framings may trigger different reactions. As suggested by the Variable Frame theory, different frames vary in their power to make a message salient and meaningful in a particular context[19, 20]. This raises concern regarding the power of nudges delivered via an e-prescribing systems, which display information that is largely insensitive to contextual factors. One needs to be very careful about generalising the findings from the study as this was a single-site study and was conducted in only one pair of medicines. The data on the time spent by the prescribers on the warning screen (nudge) were not captured during the study, this is one of the major limitations of our study. We recommend further studies include them as part of their evaluation.

Conclusion

Presenting cost information to nudge cost-effective prescribing is possible even when the actual cost of medicine is confidential and cannot be displaced. Comparative costs of expensive medicines and cheaper alternatives can be presented in form of percentile differences of modelled costs to the health care system. We developed and implemented such interventions in a pair of medicine. However, we were unable to significantly switch prescribing of expensive medicine to an equally effective, cheaper option. Further studies which may plan to evaluate such interventions should also try to capture the amount of time the prescribers spend on the screen with prompts/cues or other types of nudges.

Author Contributions

Conceptualization, Saval Khanal, Kelly Schmidtke, Usman Talat, Asif Sarwar and Ivo Vlaev;
Data curation, Saval Khanal and Asif Sarwar; Formal analysis, Saval Khanal; Funding
acquisition, Kelly Schmidtke and Ivo Vlaev; Investigation, Saval Khanal, Kelly Schmidtke,
Usman Talat, Asif Sarwar and Ivo Vlaev; Methodology, Usman Talat; Project administration,
Ivo Vlaev; Resources, Ivo Vlaev; Supervision, Kelly Schmidtke and Ivo Vlaev; Validation, Kelly
Schmidtke; Writing – original draft, Saval Khanal; Writing – review & editing, Kelly
Schmidtke, Usman Talat, Asif Sarwar and Ivo Vlaev.

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Institutional Review Board Statement

The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Human and Social Sciences Research Ethics Committee, The University of Warwick, United Kingdom (Ref: HSSREC 185/20-21).

Informed Consent Statement

Not applicable

Data Availability Statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

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Conflicts of Interest

The authors declare no conflict of interest.

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