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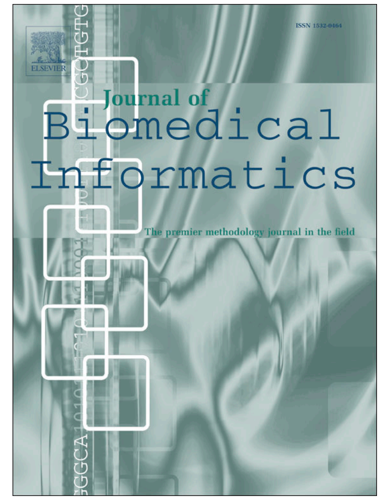

Developing and testing a discrete event simulation model to evaluate budget impacts of diabetes prevention programs

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Developing and testing a discrete event simulation model to evaluate budget impacts of diabetes prevention programs

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ABSTRACT

Type 2 diabetes (T2D) is one of the most rapidly increasing non-communicable diseases worldwide. Lifestyle interventions are effective in preventing T2D but also resource intensive. This study evaluated with discrete event simulation (DES) the relative budget impacts of three hypothetical diabetes prevention programs (DPP), including group-based contact intervention, digital program with human coaching and fully automated program. The data for simulation were derived from research literature and national health and population statistics. The model was constructed using the iGrafx Process for Six Sigma software and simulations were carried out for 10 years. All simulated interventions produced cost savings compared to the situation without any intervention. However, this was a modeling study and future studies are needed to verify the results in real-life. Decision makers could benefit the predictive models regarding the long-term effects of diabetes prevention interventions, but more data is needed in particular on the usage, acceptability, effectiveness and costs of digital intervention tools.

Keywords: Discrete event simulation, diabetes prevention, budget impact analysis, health behavior change

Highlights:

- The developed model may inform design and implementation of preventive interventions
- Discrete event simulation is an applicable method for modeling intervention processes
- The model should be verified to real life and validated with empirical data

INTRODUCTION

Type 2 diabetes (T2D) is one of the most rapidly increasing non-communicable diseases worldwide [1,2]. Globally, 463 million people have diabetes, and 10 % of health expenditure is spent on diabetes [3]. Obesity and population aging are major reasons for increasing incidence of diabetes [4]. In Finland, about 10 % of adults aged 30 or older have diabetes, and almost 70 % are overweight or obese [5]. The proportion of obese adults in Finland has increased from 12 % to 20 % during the past 20 years. This percentage almost equals elevated diabetes risk that is 18 % for men and 21 % for women aged 30-64 [5].

Diabetes has detrimental effects on individuals’ health and induces high costs for society [3]. Adopting or maintaining a healthy lifestyle is an effective way to prevent onset of type 2 diabetes [6-10]. Healthy diet, physical activity (≥150 min/week) and weight loss (≥5-7 %), can decrease diabetes risk by even 60 % among the high-risk population [11]. However, lifestyle change is a demanding process that often needs to be supported by lifestyle programs. Diabetes prevention programs (DPP) are evidence-based lifestyle interventions that usually last 6-24 months, include 10-16 meetings, and provide practical health information, help in goal setting, social support and feedback on behavior [6-9]. Although DPPs are effective, they are also expensive and not available to all [9].

Digital interventions (i.e. mobile- and internet-based programs) are not so restricted by resources but can still include many similar features than face-to-face (F2F) programs [12-14]. The effectiveness of these programs has been shown to be comparable to in-person interventions, as mean weight loss in F2F-programs has been 3-5 % [6,9,10], and 2-4 % in digital interventions with human coaching [12-14]. Regardless of delivery mode, a challenge in lifestyle interventions is how to help people to adopt and maintain self-directed behavior changes. Dropout in F2F interventions has been usually lower (10-20 %) than attrition in digital programs (25-30 %) [6,13-15]. Person-to-person interaction either offline or online is recommended as it enhances commitment to long-term behavior changes. Human interaction may promote the experience of being listened to, accountability and empathy [16]. Therefore, current research recommends use of digital interventions together with human interaction rather than using digital tools alone [17].

However, interest in fully automated lifestyle coaching has increased, as these interventions can be flexible and cost-effective. New applications, such as artificial intelligence (AI), have also enabled the development of personalized and adaptive behavior change support systems [15,18,19]. These systems can learn from users' behavior and provide tools for risk assessment, self-monitoring and feedback, as well as generate motivational messages. Results are promising but evaluation of long-term effectiveness and cost-effectiveness is missing [19]. One RCT indicated that mean weight loss in a 6-month intervention was 3.26 kg (2-3 %), and one third (35 %) of participants achieved the goal of 5 % weight loss [15]. A report from the Institute for Clinical and Economic Review (ICER) emphasized that there is much uncertainty in the effectiveness and cost-effectiveness of fully automated interventions. It is also unclear who will benefit and who are willing to use these types of programs [20].

Given that there are gaps in the research knowledge, the best way to evaluate potential benefits and challenges of new technology is the use of simulation models [21,22]. Discrete-Event Simulation (DES) is a computational method that enables the description of operations at a very detailed and real-world manner. DES does not automatically provide an optimal solution but it allows the construction and evaluation of different "what-if" scenarios. By comparing different implementation options with the as-is operation and with each other, it is possible to choose the most cost-effective proposals for piloting and implementation. Lifestyle interventions consist of many adaptive elements that influence the effectiveness and costs of the program. Recent systematic review from Leal et al. (2019) analyzed studies that evaluated economic impacts of diabetes prevention [23]. The most often used modeling types were microsimulation models, decision trees and cohort Markov models [23]. These models simulated development of health risks and changes in health status when screening, behavioral intervention or medical treatment were provided. Disease pathways were simulated from healthy to prediabetes and diabetes, or possibly, to death, using various risk factors (e.g. age, BMI, HbA1c) as predictors. However, the interventions have been treated as "black-box" entities. DES is a tool for describing also functional components and processes of interventions, which may provide essential information for decision makers.

The aim of the present study is to evaluate the budget impact of different diabetes prevention interventions using DES. The research questions are: 1) What are the relative budget impacts of different diabetes prevention interventions compared to the situation without any intervention? 2) How are the costs distributed during the intervention (eg. screening, implementation and follow-up), 3) What is the savings ratio of the interventions?

METHODS

Basic principles

Intervention processes are described in the DES model as a series of events over time. The duration, relevant resources, all the actions and costs can be defined for each event separately. In addition, the relationships and connections between different phases of the process can be described with all the routing probabilities. In DES, it is also possible to classify the entity group very precisely and set individual attribute values for each entity. These values can be used to guide the entities through the process via individual paths. The frequencies and durations of different phases are formulated as statistical distributions. The effects of different solution proposals can be examined from different perspectives (operational and economic indicators). In this article the most essential target variable are the costs. The emphasis on the determination of the savings potential of the various interventions, considering the costs of the intervention (investments, etc.), and comparing them with the costs of illness and treatment of the disease.

Simulation model

The DES model was constructed using iGrafx Process for Six Sigma. The program is designed for DES implementation, although its emphasis lies on industrial processes. Despite being focused on different fields, it still provided a useful tool for designing and implementing the desired DES model. First, the basic idea of the model was constructed using literature (Supplement 1: Appendix 1). Then the model with all the desired nodes and connections was drawn using the graphic interface of iGrafx (Supplement 1: Figure S1). After that, the functionality of the nodes was constructed again based on literature. Then the cost parameters were added, and the model was ready to run. Finally, after several iterations, the model worked as desired without any known bugs and we were able to gather the results. The model was run with four desktop computers using 3.4 GHz processors. The results of simulations were exported to the Excel spreadsheet where formulated as tables and figures.

Input data

A literature review was conducted to collect data for constructing the model structure and to extract input parameters for effectiveness. The data were collected from three main sources: 1) research literature, 2) grey literature (e.g. annual reports on diabetes) and 3) national health and population statistics. We searched systematic reviews, meta-analyses and individual studies evaluating effectiveness and cost-effectiveness of digital diabetes prevention programs (Supplement 1). We extracted input data on change in body weight (%), HbA1c, adherence to interventions and drop-out, as well as correlation between weight change and change in HbA1c (Supplement 1: Table S1).

The simulation model was developed according to the DPP protocols identified in the literature review [10,24,25]. Cost data were collected from national information sources and costs were evaluated from the healthcare perspective (Supplement 1: Table S2). Annual cost of diabetes per patient based on the estimation of Finnish Diabetes Association (2017). However, the simulation does not uncharacteristically follow resource limitations. The purpose was to examine the budget impacts of different interventions, and this was easier to analyze by disregarding the resource limitations in this phase. Further, the exact limits of resources are not constant but tend to fluctuate depending on such reasons as political will, general welfare or larger societal and environmental issues. The simulation models did not include the development costs of the interventions, resources needed for programming and maintenance of digital systems, administrative costs or other indirect costs of carrying out interventions.

Intervention parameters

Simulated population was generated based on age and gender distributions in Finnish population, population growth, morbidity and mortality, and health behavior trends (Supplement 1: Appendix 2). The parameters and threshold values of being categorized as having prediabetes or diabetes and intervention costs were described in the supplementary material, as well as other assumptions for selection of interventions and intervention processes (Supplement 1: Tables S3-S7). The purpose of the model was not to simulate absolute intervention effects in certain population cohorts but to compare relative effects of implementing different interventions

Model structure and intervention phases

The model consists of four main events: 1) risk group screening, 2) selection of intervention, 3) implementation of intervention and 4) maintenance and follow-up period. Execution of intervention comprised following sub-events: setting a goal, guidance, self-training and follow-up screening (Figure 1). The structure of the full model is presented in the supplement (Supplement 1: Figure S1).

Screening

The model entities (individuals at risk) are created in the first phase of the process called "risk group screening". After this phase, the model contains two different routing options. Entities are either guided to the "selection of intervention" or the "no-intervention" node. Screening phase determined the amount of individuals entering the interventions. Next steps in the model were affected by the event related probabilities (e.g. drop-out, extra coaching) and costs. The number of simulated participants and the probability that individuals at risk will engage in the interventions were drawn from national research reports [5,26]. In this model, 5 % of individuals whose FINDRISC score was greater than 15, entered to the "selection of interventions" node. Although resource limitations were not followed, they were taken into account in determining the size of the intervened population and the interventions offered. F2F and digital DPP with human coaching are the most constrained resources and they cannot be available to all. Estimated capacity to deliver interventions was based on previous Finnish studies [26,27].

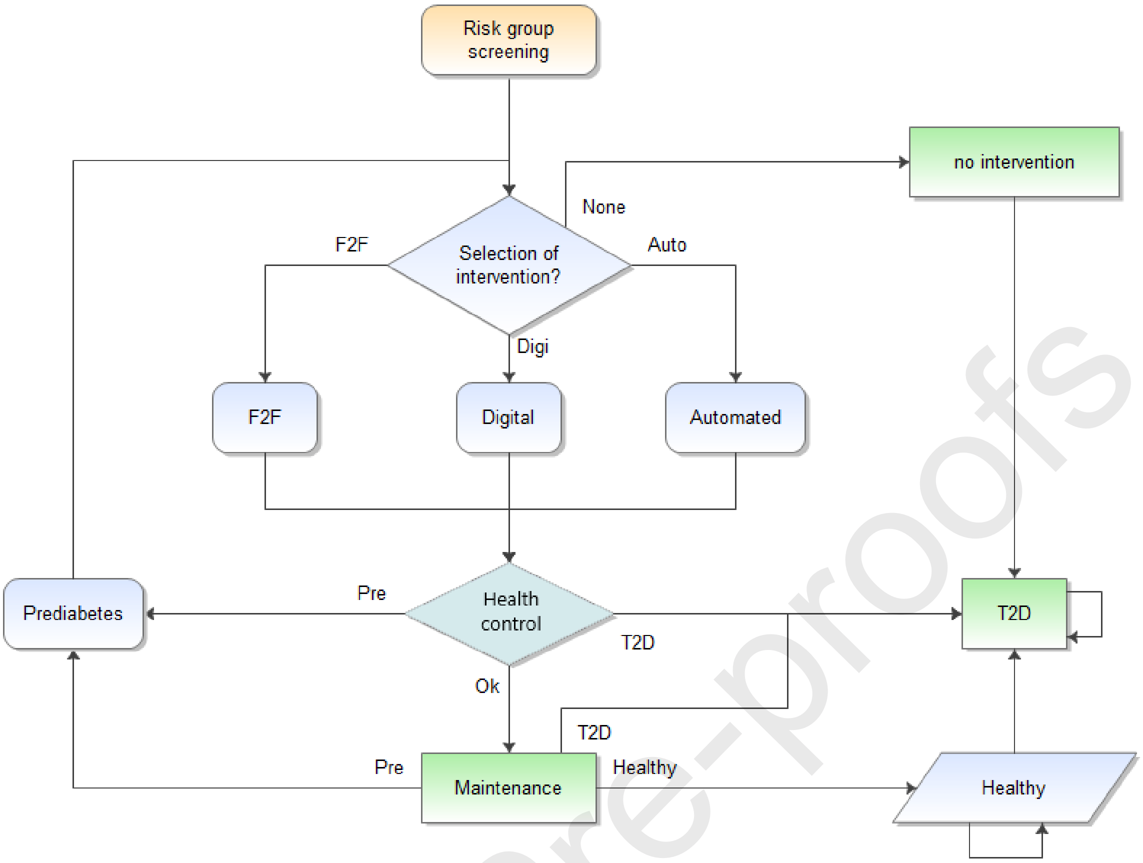


Figure 1. A simplified structure of the DES model. F2F=face-to-face diabetes prevention program (DPP), Digital=digital DPP, Automated=fully automated DPP, T2D= Type 2 diabetes

Intervention

The model had three intervention paths and each intervention had similar basic structure and principles (Figure 2). Interventions were set to last 12 months, including monitoring points every 3 months. The most important health indicator was the weight change and its impact on HbA1c. At the end of the intervention, there were follow-up measurements that determined the next phase to be either maintenance, re-selection of intervention or treatment path. The decision rules of intervention routings and structure of the full model are presented in the supplementary material (Supplement 1: Table S7, Figure S1).

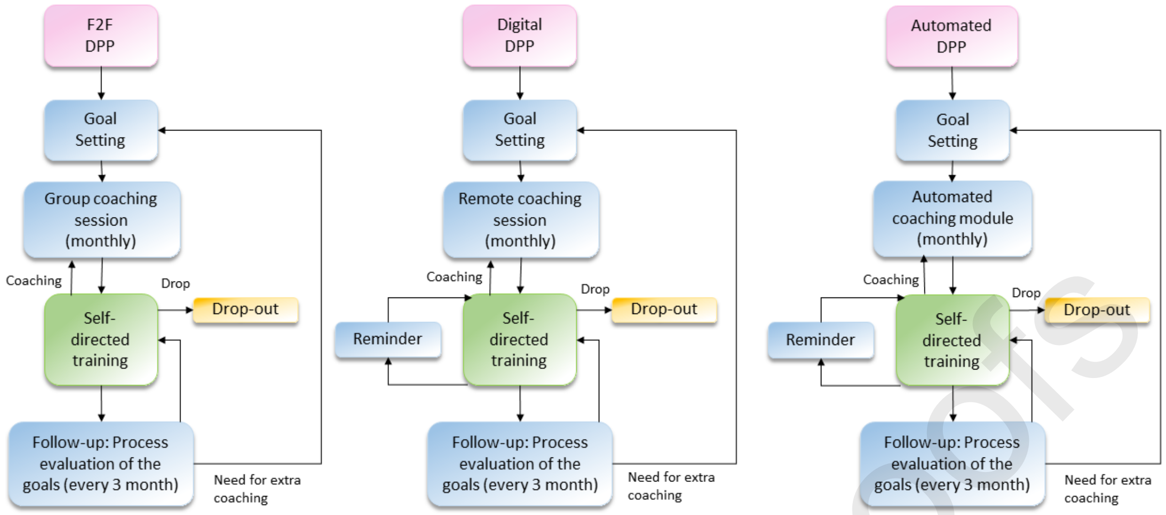


Figure 2. A flowchart of intervention events. F2F DPP= face-to-face diabetes prevention program (DPP), Digital DPP=digital DPP (with human coaching), Automated DPP=fully automated DPP

The differences across interventions were in the delivery mode, degree of human interaction, costs, effectiveness and likelihoods for drop out. Face-to-face and remotely supported interventions had interaction between professionals and participants either directly or via remote connection. In these interventions, there was also a cost associated with each control. In the automated intervention, professionals were not supposed to be directly involved in the guidance but the support was provided through an automated system. There were also monthly control times throughout the intervention. Detailed description of intervention paths and cost accumulation is available in the supplement 1.

Effectiveness of the intervention was scored the higher the greater was the proportion of participants achieving clinically significant weight loss (≥5%) [6,13-15]. Normal distribution was used to determine the magnitude of weight loss during the interventions.

Maintenance

Individuals entered the self-directed maintenance phase after the intervention. This phase was similar in each intervention, and it included a control meeting with a health professional every six months for 3 years. After that, healthy participants entered to the "healthy" node and participants who met the prediabetic criteria were guided for further interventions. In all intervention paths, some quit and throughout the simulation, some may become ill or die at any node (Supplement 1: Table S7).

Weight change in the maintenance phase was normally distributed based on previous study [28]. If an individual regains more than 2 % of initial weight he/she is directed to extra counselling. Due to lack of data, the effectiveness of extra counselling was not simulated, only the costs. Every other meeting included lab tests and if those indicated a new case of prediabetes or diabetes, the individual was directed back to the intervention paths or diabetes care path, respectively. Health status was modeled over three years. If an individual did not have diabetes or prediabetes, one was directed to the “healthy” node (Supplement 1: Table S7).

Disease costs

Individuals who get diabetes at any point of time, entered the diabetes care path, and thereafter the cost of care was €3036/year [29]. If one was directed to the “healthy” node, one remained there unless he died or developed a new case of diabetes. Since there was insufficient data on post follow-up HbA1c development, the values had to be estimated. This estimated normal distribution was based on the follow-up values and the values used in the “no intervention” node.

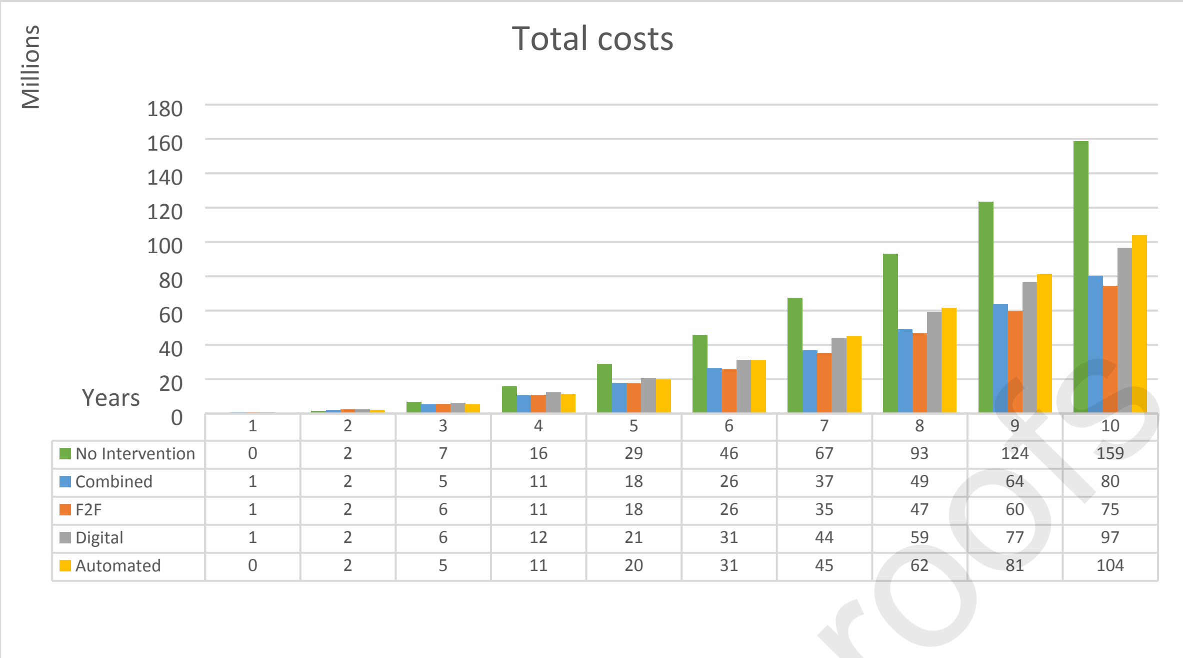
No-intervention

In addition to the three different intervention models, a no-intervention model (standard situation) was also constructed to provide a baseline for the effectiveness. The no-intervention model included all the same paths as individual intervention models with similar likelihoods of passage. The development of diabetes followed the same likelihoods as in the no-intervention node. The only cost in the no-intervention model was the treatment cost of diabetes (Supplement: Table S7).

RESULTS

Intervention versus no-intervention

The model evaluated relative budget impacts of three different interventions over a 10-year time. The results demonstrated that total costs of the interventions were initially higher than in the standard situation (“no intervention”) but from the third year onwards, the total costs of interventions remained lower than the standard situation. The costs of both models increased throughout the 10-year period (Figure 3). All the interventions produced considerable savings and their costs were closer to each other than the cost of the no-intervention option. The increase in the total cost of interventions was also higher, the lower the initial costs were. This trend can be seen in the model from the sixth year onwards.



Years	1	2	3	4	5	6	7	8	9	10
No Intervention	0	2	7	16	29	46	67	93	124	159
Combined	1	2	5	11	18	26	37	49	64	80
F2F	1	2	6	11	18	26	35	47	60	75
Digital	1	2	6	12	21	31	44	59	77	97
Automated	0	2	5	11	20	31	45	62	81	104

Figure 3. Total costs of interventions including the cost of diabetes care. F2F= face-to-face diabetes prevention program (DPP), Digital=digital DPP, Automated=fully automated DPP, Combined= combination of all interventions

Comparison of interventions

The model compared the costs, saving potential and functionality of the interventions and their combinations. Figure 4 presents the total costs caused by the interventions and their division between screening, intervention and follow-up. Costs of health controls and follow-up at maintenance were almost similar, but the difference is in the implementation of interventions.

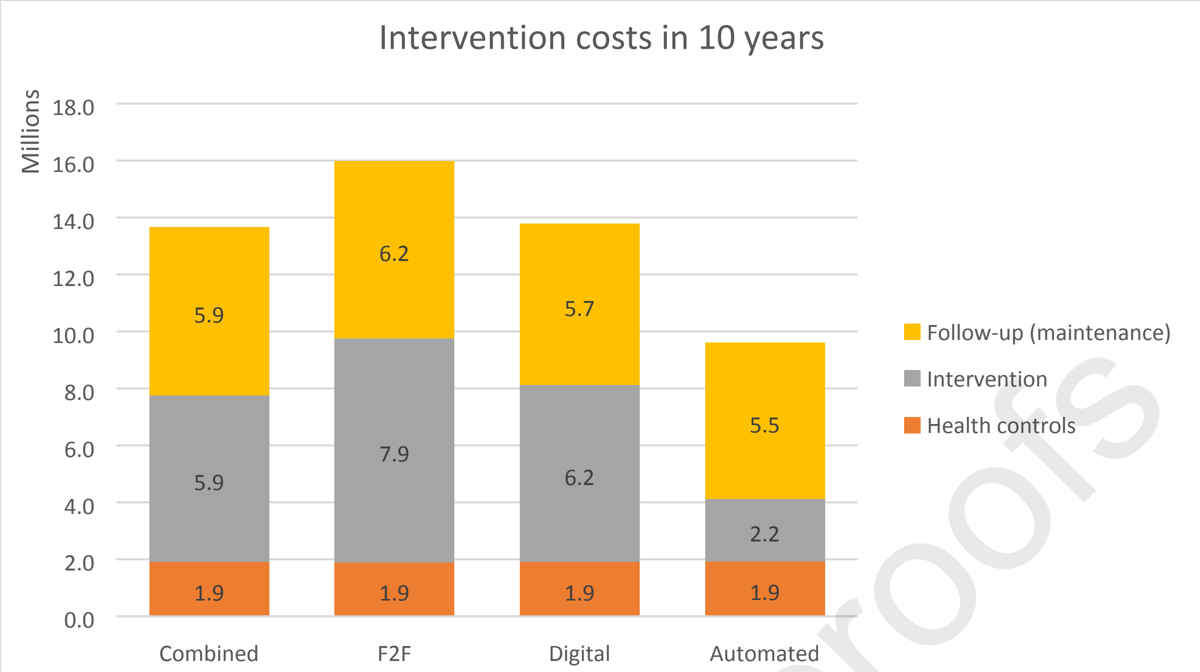


Figure 4. Intervention costs and distribution of costs in 10 years. F2F= face-to-face diabetes prevention program (DPP), Digital=digital DPP, Automated=fully automated DPP, Combined= combination of all interventions

Figure 5 presents the savings of different interventions in the 10-year period compared to the situation where no intervention is carried out. Each intervention started to generate savings after three years. Another important aspect is the correlation of costs with savings. The more expensive the intervention, the greater the savings were. Face-to-face intervention generated the biggest savings when compared to no intervention. The savings potential was slightly under 53% (Figure 6). The second biggest savings was achieved by a combination of all interventions. The smallest savings, still more than one third of the costs of not intervening, were obtained with fully automated intervention.

Figure 5. The total savings generated by the different interventions. F2F= face-to-face diabetes prevention program (DPP), Digital=digital DPP, Automated=fully automated DPP, Combined= combination of all interventions

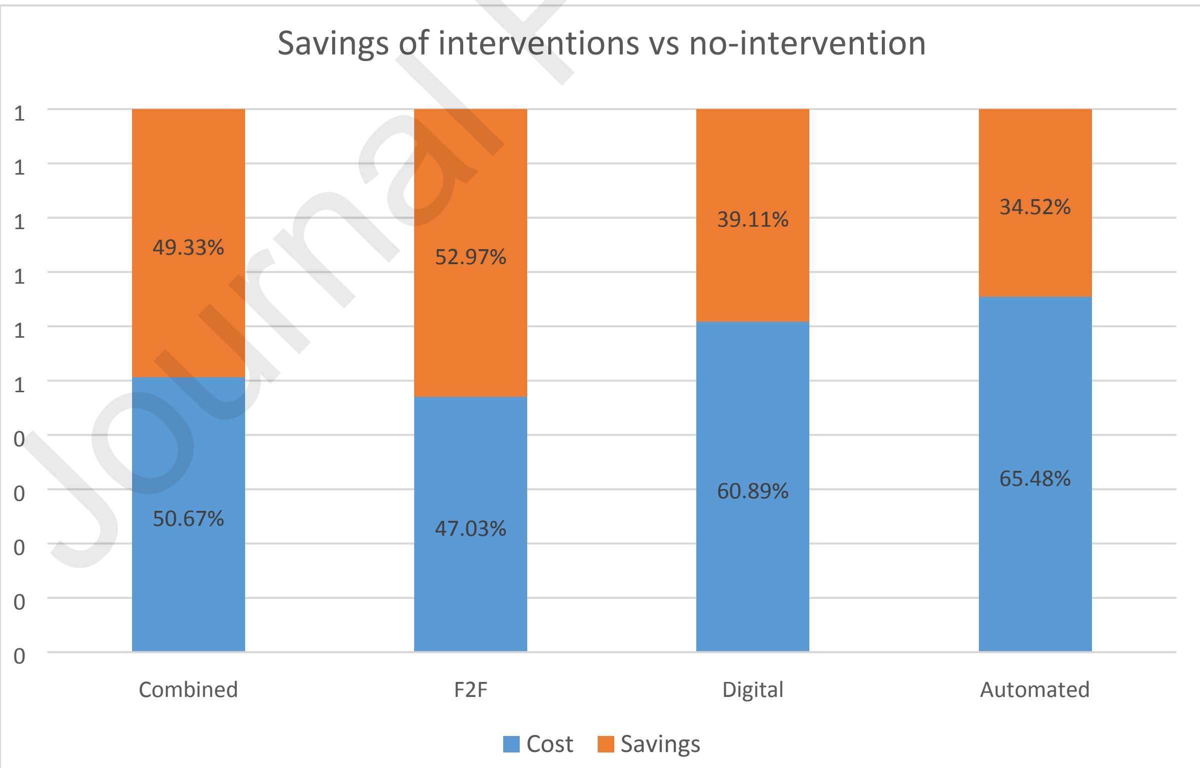
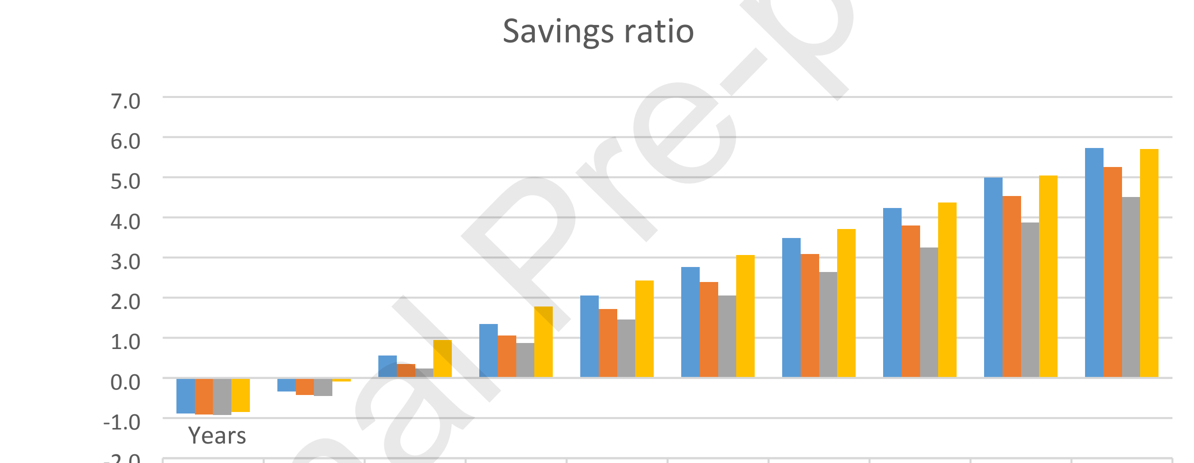


Figure 6. Achieved savings of interventions (%). F2F= face-to-face diabetes prevention program (DPP), Digital=digital DPP, Automated=fully automated DPP, Combined= combination of all interventions.

The savings ratio describes how many euros are saved for each euro invested (Figure 7). On the zero line, the savings correspond to the additional costs caused by intervention, at level 1 the savings were equal to additional costs, etc. Figure 7 shows that from the third year onward the savings exceeded the costs. It is also noteworthy that all interventions generated savings and the savings ratio was growing steadily.

The low cost of implementation makes automated intervention perform much better when comparing interventions using the savings ratio instead of total savings. Still, its growth rate was poorer and by the tenth year, the combination of all interventions (group-based, digital and fully automated) overtakes it at the top. Based on a 10-year simulation, also group-based intervention was expected to score better than automated before 20 years of implementation.



	1	2	3	4	5	6	7	8	9	10
Combined	-0.9	-0.3	0.6	1.3	2.1	2.8	3.5	4.2	5.0	5.7
F2F	-0.9	-0.4	0.3	1.1	1.7	2.4	3.1	3.8	4.5	5.3
Digital	-0.9	-0.4	0.2	0.9	1.5	2.0	2.6	3.2	3.9	4.5
Automated	-0.8	-0.1	0.9	1.8	2.4	3.1	3.7	4.4	5.0	5.7

Figure 7. Savings ratio of compared interventions. F2F= face-to-face diabetes prevention program (DPP), Digital=digital DPP, Automated=fully automated DPP, Combined= combination of all interventions

DISCUSSION

Main findings

The purpose of the study was to evaluate budget impacts of diabetes prevention interventions among high-risk individuals. The results demonstrated total costs, distribution of intervention costs, savings and savings ratio.

The first aim of the simulation was to estimate what are the relative budget impacts of different diabetes prevention interventions compared to the situation without any intervention. This case showed that the more expensive the intervention was, the more it generated savings through avoided diabetes cases in ten years. From the third year onwards, the costs of all interventions were lower than without interventions. The savings potential in ten years was about 50 % for F2F intervention and for the combined model. Given that we did not consider all potential costs or resource limitations of simulated interventions, these results should be interpreted with caution.

The second question of interest was how the costs are distributed during the intervention process. Comparable costs considered intervention events (e.g. health coaching), health controls and follow-up measurements. Costs of health controls and maintenance support were almost similar, but implementation of intervention was the most expensive in the F2F program. However, when total savings of interventions were compared, F2F outperformed other interventions due to better prediction of effectiveness. The savings potential compared to the situation without interventions was about 50 % for F2F program and combined intervention model where all intervention alternatives are available. From the practical perspective, the combined model would be the most reasonable, as it may have greater scalability and ability to meet different individual needs.

Savings ratio of different interventions and their combination was the third research question, and also this analysis indicated that the combination of F2F, digital and fully automated interventions could produce the best savings, nearly six units per one unit invested. The next best savings ratio was in the fully automated program due to minimal costs of intervention delivery. However, its simulated costs grew faster than in other cases suggesting that during the longer time horizon, the savings ratio would decline.

Comparison of results to the previous research

The used method, a discrete event simulation (DES), appeared to be a feasible for economic evaluation and modeling the intervention processess. The results showed that simulation worked as expected, as all the interventions prevented diabetes and reduced the cost of the treatment. This was in line with previous modeling studies, of which majority have reported that lifestyle interventions are cost-effective when compared to usual care or no intervention [23]. However, only a few of these studies have compared different intervention types (digital vs in-person), and none used DES as a simulation method.

Some studies have compared the costs or cost-effectiveness of online intervention with individual or group-based coaching [14,30]. Little et al. (2017) reported that the probability of being cost-effective at a threshold of £100 per kilogram was 98% for the online program with remote human support when compared to the stand-alone online program. Similarly, F2F programs have been estimated to be highly cost-effective when compared to control situation with no-intervention [31].

A report from Institute for Clinical and Economic Review (2018) compared budget impacts of three DPP types, and the authors concluded that group-based in-person intervention would have the most favorable budget-impact when compared to the in-person individual coaching and digital coaching with human support [20]. Both group-based in-person coaching and digital coaching were estimated to produce cost savings. The results are in line with our findings, but the study had also the same problem: There was limited input data on fully automated programs. Only recently, one systematic review summarized cost-effectiveness of mobile DPPs [32]. This study showed that there are high variability in used technology and costs, but majority of studies reported high cost effectiveness. However, the role of fully automated programs in prevention of diabetes and increasing cost-effectiveness remained unclear.

The results of the present study are influenced by the model structure, input parameters, assumptions of effectiveness and used routing probabilities. The majority of the very high-risk individuals were directed to the contact intervention and only one fifth to remote support intervention. Very high-risk individuals were not guided to fully automated intervention. The costliest intervention (F2F intervention), has been proven to be also the most effective [6,19]. Thus, when selecting the best intervention for very high-risk individuals, contact intervention seems to provide significant benefits.

If there were an unlimited number of care personnel, contact intervention would be very effective in reducing morbidity and, in the long term, would save the treatment costs. In practice, resources are limited, or not all individuals want to participate in F2F-intervention. Extending the range of interventions with digital services seems to be a worthwhile alternative from the point of view of both customer orientation and costs.

It is noteworthy that the cost-saving ratio of the model combining all implementation methods proved to be better than any intervention alone. However, the simulated budget impacts did not consider the costs of development, programming or maintenance of digital systems. The administrative costs or other indirect costs of carrying out interventions were neither taken into account. On the other hand, prevention produced savings despite that the model included a long follow-up after an active intervention. At a larger scale, such an intensive and long follow-up period would not be possible for all. Digital tools may be used with greater extent to deliver long-term support for self-monitoring and maintenance of lifestyle changes.

Strengths

To our knowledge, this is the first study applying DES in evaluating budget impacts of diabetes prevention interventions. Other types of simulation models (e.g. Markov-models, decision trees, system dynamics and agent-based) have been increasingly used in behavioral sciences [23], but DES has been less often applied [33]. Markov-models have been criticized for being static, while constructing a more detailed simulations, such as system dynamic models are complex processes, requiring a comprehensive amount of qualitative and quantitative data [21,34]. Lifestyle choices take place in a broad socio-ecological system, which justifies the use of system dynamics or agent-based models in modeling behavioral changes [34]. However, DES can be a suitable method when there is a need to find a balance between complexity, computability and real-life validity of the model [21,33].

This study showed that DES is a relatively straightforward and feasible approach for modeling lifestyle interventions, but an essential part of the process would be ongoing validation to real life when more accurate and relevant data become available. This requires co-operation with different stakeholders in planning, implementation and evaluation of interventions. Decision makers could benefit predictive models regarding the long-term effects of diabetes prevention intervention. However, more data is needed in particular on the usage, acceptability, effectiveness and costs of digital intervention tools. A strength of DES is its ability to inform decision making not only about the total costs of the intervention but also the stress and resource needs that the system encounters during the implementation phase.

Limitations

The DES model was constructed according to the evidence-based intervention protocols and most of the parameters were drawn from the peer-reviewed research or national population and health statistics. However, the study had several limitations related to data, model structure, assumptions, assessment of uncertainty and used modeling tools.

First, comparable follow-up data were not available for each intervention type. To our knowledge, long-term effectiveness on fully automated interventions has not been evaluated to date. The use of invalidated estimates may overestimate the effectiveness of automated programs and underestimate their costs. The simulation suggested that the preferred way to implement interventions is to provide all options in combination, rather than conducting stand-alone programs. This is in line with current research that recommends use of digital interventions together with in-person communication [19]. Automated support is likely to be the least effective but it may be still a noteworthy option and an easy-to-access alternative for some groups.

Second limitation is low availability of local data on digital interventions. At the time the modeling was carried out, the effectiveness of digital diabetes prevention intervention was not evaluated in Finland [35]. Therefore, we used aggregate data from international and national references. This may decrease the validity of the results in the Finnish population. However, the reference studies were from high-income countries, which improves the external validity [14,15]. The unit costs were from national studies and healthcare reports, although the costing data was not very recently updated. Technology development and increased use of digital tools during the past decade may have influenced the cost level.

Third limitation is poor data availability on implementation processes of the digital interventions. Therefore, we had to use rough estimates for some routing parameters in the model. Individual preferences on choosing the intervention was omitted due to lack of data on this topic. Selection of an intervention was instead substituted with the 80/20 rule as a directional rule of thumb. Also omitted were the possibility to change intervention paths and the availability of fully automated intervention to those individuals who either would opt to choose one of the more resource-intensive paths but due to lack of resources must wait to get in, or would prefer it although they are eligible to other intervention. As the model did not follow resource limitations it is not right off applicable to real-life situations. The model was constructed to show the potential of different interventions rather than to showcase actual cost-benefits in a particular setting. In the best cases, modeling can inform evidence-based practices, but lack of verification, validation and transparent documentation can hamper the benefits of using prospective models in decision-making [36]. Therefore, we strived to describe all parameters and assumptions as precisely as possible (see Supplement 1) so that the model can be replicated and developed further when appropriate data will be available.

Fourth limitation considers the model structure and assumptions. For simplicity, we assumed that all interventions had somewhat similar structure, and follow-up intervals, although there would be more variability in practice. Digital tools may enable even more real time feedback and just-in-time adaptations than modeled in the current simulation [18]. Another issue is the narrow scope of parameters used to predict intervention engagement and effectiveness. For example, we did not consider socioeconomic factors, although these are likely to impact availability of services, health promoting behaviors and likelihood for risk factors [5,26]. We did not either run alternative versions of the model with different structural or methodological assumptions that are usually included in the full economic analyses [22].

Lastly, the simulation program had its limitations due to not being designed for this particular case. While adequate, it lacked some of the desired functionality that could have been implemented if a more flexible program was used. A strength of the iGrafx tool was the possibility to use graphical interface for drawing the model. This feature may be useful when working in the multi-professional teams.

Future research

Future work should improve the validity and quality of the model using empirical data. Further data is needed on intervention processes, population-based risk factors, adherence to interventions and actual intervention costs. Given that the purpose of the modeling studies is to make predictions and evaluate future scenarios despite incomplete information, the next challenge is to develop the model so that it can better manage this uncertainty. This work provides a basis for developing a tool for decision-making, but the simulation model would be more flexible and better-maintained if the model was self-programmed, e.g. by using Python. Future study will evaluate how simulation, optimization and machine learning could be integrated when developing a decision support system for diabetes prevention. Future studies would also extend the model functions so that it could predict the risk progression of other non-communicable diseases (e.g. cardiovascular diseases).

Conclusions

The study used the discrete event simulation (DES) to assess budget impacts of three hypothetical diabetes prevention programs (group-based contact intervention, digital program with human coaching and fully automated program). The results showed that DES is a feasible method in evaluating intervention effects but data that is more comprehensive is needed for a realistic model. Future studies should improve the validity and accuracy of the model.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Highlights:

- The developed model may inform design and implementation of preventive interventions
- Discrete event simulation is an applicable method for modeling intervention processes
- The model should be verified to real life and validated with empirical data