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Identification of child mental health problems in primary care: an interdisciplinary approach

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Chapter 8

General discussion

General discussion

The main objective of this thesis and the Pippi-study was to improve the early identification of child mental health problems (MHPs) by developing a prediction model for child MHPs, with readily available information from electronic health records from general practice. In addition, we investigated whether combining electronic health record information from general practice and preventive youth healthcare (PYH) would result in better prediction of adverse mental health events in children.

In the current chapter, we first describe the main findings of this thesis by relating them to the case of Tess, who was introduced in chapter 1. Considerations regarding the used data, the methodological approach and developments in current research regarding prediction models will be discussed thereafter. We will then elaborate on considerations regarding the early identification of child MHPs and the clinical implications of this thesis. Finally, we will give recommendations for further research, before presenting our conclusion.

Main findings related to the case of Tess

To illustrate the dilemmas general practitioners (GPs) can face when identifying child MHPs, the case of Tess was presented in chapter 1

Tess, 14 years old
Tess visited her GP Julia, because of depressive feelings and a declining school performance. A lot appeared to have happened in Tess's family situation in the previous years, which might have influenced Tess's current situation. Other than occasional visits for common complaints, Tess's medical history mentioned several visits for constipation. Julia referred Tess to secondary mental healthcare for further treatment but wondered whether she could have seen Tess's mental health problems coming earlier.

As all GPs in the Netherlands do, Tess's GP uses an electronic information system to store the medical records from her patients. With these readily available data, we built a prediction model for child MHPs, which could be applied to Tess's electronic medical record (EHR). The goal of the model was to automatically calculate Tess's risk

of developing an MHP based on the available data in her EHR. At the time Tess visited Julia or one of her colleagues for constipation, it would have been possible for them to use the model to see Tess's risk of developing an MHP. The GP might have taken the opportunity to approach the constipation differently, with more attention to the context.

The prediction models we developed in chapter 3, however, were not able to give a clear indication of whether Tess was at risk of developing MHPs. In their current form, the models need further improvement before they can safely be used in daily practice. Nonetheless, individual characteristics from EHRs such as somatic complaints (including constipation and headache) and factors related to a higher healthcare use appeared to be age-independent risk factors for child MHPs. Awareness of the presence of (a combination of) these risk factors can inform GPs about the vulnerability of a child to develop MHPs. The GP seeing Tess regarding her constipation could already have been alerted to her vulnerability and the GP might have taken the opportunity to explore Tess's mental wellbeing and context further.

In addition, we found that some information regarding already known predictors for child MHPs that involve the child's family and environment, could not be extracted from the data due to incomplete registration. Whether the GP would suspect psychosocial factors to play a role and how she would explore the child's context depends on the GP. We found that such inter-professional variation played a role in the identification of child MHPs by primary care professionals, which is described in chapter 2. In this systematic review we showed that the prevalence rates of MHPs identified by primary care professionals varied substantially. Primary care professionals identified between twenty-six and sixty percent of the children with an increased risk of MHPs as indicated by MHP assessment tools. Factors related to the child or the visit that made identification of MHPs by primary care professionals more likely were a family composition other than married parents, severe mental health symptoms, prior MHPs, male gender in elementary school, preventive well-child visits or visits to primary care professionals related to psychosocial concerns. In the case of Tess, information regarding her family situation (e.g. her parents' divorce and MHPs of her father) could have been relevant to assess her complaints. In addition, we found that professionals who self-identified as being less burdened treating MHPs and professionals who were recently trained in child MHPs were more likely to identify MHPs. Those professionals were also more likely to recognize MHPs in children with an increased score on MHP assessment tools. Our findings suggest that professionals who are trained and feel less burdened managing MHPs would have approached a child like Tess, presenting with constipation, differently than colleagues who are not trained and feel more burdened would have.

The second aim of this thesis was to explore whether combining EHR information from general practice and PYH would result in better prediction of adverse mental health events in children. The results of the study presented in chapter 5 indicate that the models that incorporated information from PYH did not perform better compared to the models based on general practice data alone. Nevertheless, several individual characteristics measured in PYH were predictors for MHPs in general practice. These characteristics include PYH concerns for MHPs, borderline or increased scores on mental health screening tools, exposure to life events, a recorded family history of MHPs in PYH data, and an extra visit to PYH. Information regarding these characteristics could still be useful for GPs in daily practice to have access to, in order to improve the early identification of child MHPs.

Relating these findings to the case of Tess, Tess would have been seen for routine appointments in a PYH setting twice in primary school and once in secondary school in the years prior to the current consultation for her depressive feelings. During these visits, mental health screening tools would have been used, and enquiries would have been made regarding Tess's development, school performance and psychosocial situation. Leaving aside potential outcomes of the mental health screening instruments, PYH might have had access to information about Tess's family situation and problems at school at an earlier stage. If this information had been shared with general practice, this might have influenced the approach that was taken during Tess's general practice visits for constipation. In addition, the study performed in chapter 6 found that the presence of PYH concerns for MHPs was also a risk factor for child and adolescent mental healthcare (CAMH) use, next to the characteristics school problems, a child being bullied/bullying or being underweight, all of which are registered in PYH.

In the qualitative study presented in chapter 7, we investigated the current collaboration between GPs and preventive youth healthcare professionals (PYHPs). We found that the current collaboration between GPs and PYHPs is suboptimal, and that structural collaboration and information exchange was often not present. With the case of Tess in mind, we explored how likely it would be that the GP who assessed Tess for constipation would have reached out to PYH for further information? Our study suggested that most professionals did not have any structural contact and contact was mostly sought in urgent cases. Therefore, we do not think PYH would have been contacted at this point: a potential missed opportunity.

Considerations regarding the data and methodology used in this thesis

Before we are able to address the implications of the findings presented in this thesis, it is important to place the data and methodology used in this thesis into perspective.

Strengths of the Pippi-study

To our knowledge, the Pippi-study is the first study to combine routine healthcare data from different sources on such a large scale for the purpose of improving child MHP recognition. In this way, the Pippi-study provided unique complementary information from the different healthcare professionals involved in the primary care for Dutch children. In recent decades, the availability of clinical data extracted from EHRs has generated new opportunities for research. Although generally gathered for the purpose of providing healthcare, the use of routine healthcare data for scientific research has several important advantages. It provides a low-cost and time-efficient way of accessing rich, real life, longitudinal data on large populations, which can be linked to data from other sources or people(1).

Other reported advantages of EHR data are, for instance, fewer systematic errors (bias) such as selective nonresponse, response bias (systematic error caused by social desirability or leading questions), and recall bias (systematic error caused by differences in the precision or completeness of the recollections of events or experiences from the past)(2).

Linkage of the different datasets

In chapters 5 and 6 of this thesis we linked the datasets from general practice to data from PYH and to data regarding CAMH use on an individual patient level. Our original cohort of general practice data from the period between 2007 and 2017 included 70,000 children, and for 91% of those children, data from Statistics Netherlands regarding CAMH use was available. For approximately 70% of the children included in the original general practice cohort, data extracted from PYH could be individually linked to the general practice data. All children with both general practice and PYH data could be linked to data from Statistics Netherlands.

Data from general practice could not be individually linked to data from PYH of Statistics Netherlands when either no unique Dutch citizen service number (burgerservicenummer, BSN) or a wrong BSN was present in the databases. In the early years of the general practice cohort, it was not yet legally required to register a child at a general practice with a BSN(3). In addition to a missing or incorrect BSN number, the fact that children can go to secondary schools outside their PYH region, meaning they are monitored by

a different regional PYH, was another reason why data from GPs and PYH could not be linked for some individual patients. There were, however, no major differences in the characteristics of the children with and without PYH data. Therefore, we do not expect that a successful linkage between data from GPs and PYH for 70% of the children has altered our findings.

Generalizability of the Pippi-study

Most Dutch inhabitants are registered with a general practice. We therefore expect our cohort to be a fair reflection of the general Dutch population, including minority populations (either ethnic or socio-economically defined) that are known to be underrepresented in studies that actively recruit patients(4).

In addition, Dutch GPs are the gatekeepers to secondary healthcare. We assume the findings related to the general practice data to be fairly generalizable to countries with a similar, gatekeeper healthcare system, such as the United Kingdom(2). In general, when transporting a developed prediction model to another setting, one should look at factors that are related to the transportability of a prediction model, for example changes in patient characteristics, changes in administered treatments and changes in predictor measurement procedures(5). External validation of developed prediction models is therefore recommended(6).

We are aware that the PYH data we used in this study is specific to the Dutch healthcare system and the registration used in this particular region. That said, many countries do have a form of preventive youth healthcare or well-child clinic that monitor a child's healthy development(7-9), and validated mental health screening instruments are widely used(10). We think our findings can therefore still serve as a starting point for research regarding the use of EHR data for the early identification of child MHPs, when the approach is adapted to the local healthcare system and digital registrations used. The same holds true for the data regarding CAMH use.

Model development

The available EHR data contained an abundance of information and many potential predictors that could be included in a prediction model. Popular strategies to reduce a set of potential predictors during model development include stepwise selection methods, such as a backward selection of predictors based on a certain p-value(11, 12). These statistical selection methods do have disadvantages and it is advised to consider literature and clinical knowledge when selecting predictors for model development, rather than solely rely on statistical selection methods(6, 11, 12). Much is already known regarding the multiple risk factors for developing child MHPs. Given the above, we

developed models that incorporated the existing subject matter knowledge, including the results of our systematic review, and perspectives from various professionals working with children in clinical practice by means of an expert panel(13).

Limitations related to the use of EHR data for research purposes

Data primarily recorded to facilitate patient care

The information stored in EHRs is generally not collected in a standardized way, as it is primarily recorded to document and facilitate the care of individual patients rather than for scientific purposes. Regarding the data from general practice, registration of information depends on both the patient and the GP. The patient first has to decide to visit the GP and mention specific complaints, and it then depends on the GP which information is recorded and how this information is registered or coded in the EHR. These factors might affect the completeness and accuracy of EHR data. In the Netherlands, the International Classification of Primary Care (ICPC) coding system, which facilitates consistent recording, is built into EHR systems together with a guideline describing what should be recorded in an EHR system and when(2, 14, 15). Over the years the quality of the general practice EHR data has therefore improved(16).

The data from PYH differed from the general practice data since it concerned data from scheduled, standardized visits in which certain aspects of a child's healthy development should be monitored. However, it is known from the field that professionals have a lot to register during consultations, and that it again depends on both the professionals and the child which information is being recorded. There is no standardised coding system available yet and PYHPs can record a lot of information as free text. As with the GP data, we expect that PYH data quality will improve over time. At present, PYH in the Leiden area has implemented a new EHR information system in daily clinical practice and emphasis is being placed on the importance of correct recording of clinical information, also for research purposes. Furthermore, research is being conducted regarding the development of a national uniform basic set of diverse indicators or items regarding a child's healthy development.

Missing data

Missing data is one of the major challenges of using EHR data for research(17, 18). Missing general practice data is often missing not at random, i.e. the probability that an observation is missing depends on information that is not observed in the data(19). It is common practice to assume that a determinant or disease is not present when data is missing(18, 19). In line with this, we chose to not use multiple imputation techniques when developing the prediction models with general practice data.

One of the aims of this thesis was to explore which specific information from PYH (reflecting the structured, routine PYH visits) could be useful to exchange with GPs to enhance MHP identification. In this quest, we did not expect to find that a large number of determinants had quite some missing data, which was the case for over 80% of the children. Although a small percentage of the missing determinants could be explained by the fact that they concerned information from extra healthcare visits in PYH for a specific reason (e.g. visual problems) and not a regular visit in which standard items should be checked, this did not fully explain the magnitude of the absence. One hypothesis for the absence of this data could be that as a result of currently unknown technical issues, information from prior consultations which should be visible during later consultations in practice was not present in our extracted data. In addition, during the early years of our study period, data was transferred from paper to electronic files. All important information should have been transferred, but this migration will still have caused some gaps in the data.
As some missing PYH data could be predictive (e.g. missing results of mental health screening tools), we included a "missing" category for some determinants in chapter 4. Missingness turned out to have no predictive value.
As with the general practice data, we chose to not use multiple imputation techniques for the missing data from PYH. Imputing data missing from our extracted PYH data, eventually potentially used to share with GPs for clinical practice purposes, did not seem justifiable.

Misclassification
In the Pippi-study, we aimed to define the determinants and outcomes we investigated as specifically as possible by supplementing coded diagnoses with other information (e.g. medication prescriptions) when feasible. This was in order to increase the validity of the determinants and outcomes and to prevent misclassification(20). For the definition of the determinants based on general practice data, this was not always possible, and we found that information regarding known social risk factors for child MHPs (e.g. regarding the child's family and environment) was not available since due to incomplete registration (chapter 3). We expect that the absence of extractable information regarding these important risk factors for child MHPs will have affected the performance of the developed prediction models.

We assume some misclassification bias, i.e. when a person is assigned to a different category than the one they should be(21, 22), to play a role when looking at specific determinants, such as the presence of chronic diseases based on general practice data, we looked at in chapter 3. We expect the misclassification regarding the general practice data to be mainly related to some of the determinants (e.g. chronic disease) we investigated, and we expect

this misclassification to be non-differential, i.e. not depending on the outcome status of the patient, leading to potential dilution of the found effects(21). Regarding PYH data, the number of PYH concerns for MHPs varied greatly between different ages, meaning that misclassification regarding the outcome could not be ruled out.

In chapter 6, we investigated which children had healthcare costs in child and adolescent mental healthcare (CAMH) based on data from Statistics Netherlands. We defined the presence of CAMH costs as the first calendar year with any costs made regarding CAMH for a child. Misclassification could have happened in several instances. As we looked at any costs present, this could in theory also involve children who were only seen once in CAMH and who did not undergo treatment. We feel however, that this would concern a very small group of children and the fact that a child has been referred to CAMH already indicates more severe problems.

In addition, by calculating a timeline between a first MHP registered by the GP and the first registered CAMH use per calendar year some misclassification will have occurred. The two scenarios to note would be: 1. a child being referred to CAMH in late December of one year and first being seen in CAMH in early January of the next year, this being counted as one year difference; and 2. a child being registered in general practice with MHPs in January of one calendar year and being seen in CAMH in December of that same year, counted as the same year. In addition, it could happen that a child would have GP registered MHPs but registration of CAMH use would be outside our time-window, or vice versa. We expect that these effects will have balanced over the whole cohort and that the data from the period 2009-2015 would give a fair indication of registered MHPs in general practice and CAMH use.

One should, however, bear in mind that the waiting time between a GP's referral and the child being seen in CAMH is also included in this timeframe and that this waiting time could vary in time and between the different CAMH professionals/institutes. Our data was not specific enough to enable us to look into this further.

What is a good prediction model?

Numerous prediction models have been developed over the past few years, but only a small number are implemented in daily clinical practice. A sufficient discriminative ability (i.e. the ability of the model to distinguish between children with MHPs and those without MHPs), is the primary requirement if one wants to use the model to identify a high-risk group, as we aimed to do in this thesis(6). A model's discriminative ability,

however, is not sufficient to indicate the clinical usefulness of a prediction model. Or in other words, whether a prediction model is useful to support medical decision-making(6). Nevertheless, a lower discriminative ability makes it unlikely that a model will be clinically useful(6).

The prediction models we developed in this thesis showed a moderate performance. We are of the opinion that our models need further improvement before they can safely be used in daily clinical practice. One of the explanations for this moderate performance of the models based on general practice data is the absence of extractable information regarding some known risk factors for child MHPs in the general practice data (chapter 3).

Our hypothesis was that combining information from PYH and general practice would result in better performing prediction models for MHPs compared to models based on general practice data alone. Unfortunately, this was not the case (chapter 5). The structured registration of potential MHP predictors in PYH was less good than expected and this is most likely one of the reasons for the limited added value of combining PYH and general practice data into one decision supporting algorithm. It is difficult, therefore, to conclude that combining data from PYH and GPs to improve prediction models for child MHP identification would not be worthwhile.

Developments in current research regarding prediction models - what role can machine learning techniques play?

Applying machine learning techniques to the data might result in better performing prediction models. Machine learning (ML), techniques that focus on models that directly and automatically learn from data, have gained enormous popularity over the past few years(23). ML is claimed to have better performance over traditional statistical modelling and to better handle a larger number of potential predictors(23). With the increasing availability of large datasets, for instance from EHRs, the expectations of ML in medicine are high(24).

As previously described, the development of the prediction models presented in this thesis was approached more traditionally. Data preparation and coding of potential predictors was done manually, which was quite time-consuming. ML would provide a more efficient approach. An exploration of ML techniques in the general practice dataset resulted in prediction models with c-statistics up to 0.79(25). Some found predictors

seemed to make sense from a clinical point of view (e.g. number of visits), while others (e.g. a performed worm egg test or sex hormone medication) seemed to make less sense. Research on ML for primary care is at an early stage of maturity for practice applications(26). Attention should also be paid to the physician's point of few regarding the explainability of models incorporating ML that are potentially implemented in daily care.

However, there is evidence that ML based prediction models do not automatically lead to improved performance over traditional methods(23, 27). So how can ML support the early identification of children like Tess? A study investigating the use of primary care EHR data for identification of depression in adults showed better performing models when both structured (coded) and unstructured (free text) EHR data was used(28).

Natural language processing

As we feel that one of the explanations for the moderate performance of the developed models in this thesis is the absence of extractable information regarding some known risk factors for child MHPs, natural language processing (NLP) may be of particular interest for future research(29). NLP is a special field in ML which parses unstructured text (free text or narrative data) into structured, quantifiable variables(30). With NLP, the free text of EHRs, in which potential useful information regarding important social/contextual risk factors for child MHPs are written down, could be assessed. These free text notes in which physicians describe the patient's subjective story and symptoms were not part of the available data in the current Pippi-study. We would strongly recommend future studies to investigate free text analysis in order to improve prediction models for early identification of child MHPs.

Considerations regarding the early identification of child MHPs

Recognition of MHPs differs from the recognition of somatic diseases

Identifying child MHPs is different compared to the recognition of somatic diseases (e.g. Diabetes Mellitus), as there are no direct quantitative biomedical tests such as blood tests for mental health issues(29). Instead, physicians are dependent on signs and symptoms that children or parents report, and on observations during consultations(29). It is known that a substantial number of children with MHPs is not being recognised as such. US paediatric primary care providers' sensitivities and specificities for identification of child MHPs, for example, ranged from 14% to 54% and from 69% to 100% respectively(31).

Furthermore, mental health-related stigma plays a role in the identification and help-seeking process of MHPs(32), and this might also be of influence on the diagnostics and management of experienced mental health related symptoms or problems. Especially as children with MHPs are known to visit their GP more often for physical than psychological reasons prior to MHP diagnosis(33). In addition, children who experience somatic complaints that can be related to MHPs (e.g. headache and abdominal pain) are frequently referred to paediatricians working in secondary care to rule out somatic causes of the experienced complaints.

Can highly discriminating models that predict child MHPs be developed?

The question also is whether it is actually possible to develop a highly discriminating model that predicts child MHPs in the future. MHPs and symptoms are known to fluctuate over time, and this differs per MHP type. The widely used mental health screening instrument Strengths and Difficulties Questionnaire (SDQ) has a good concurrent discriminative ability, with a reported c-statistic of around 0.80(34). The long-term predictive value of the SDQ, however, is lower. The reported sensitivity of the SDQ sore in preschool children predicting MHPs 5 year later for instance was 35% for any MHP, with lower numbers for emotional problems and higher numbers for behavioural problems(35).

The SDQ is a specific mental health screening instrument incorporating information regarding mental health symptoms. In this light, the moderate discriminative ability of our models to predict child MHPs one year later based on general practice data, including biomedical and healthcare use information, could be valuable for the GP's decision-making process. Similar discriminative abilities of prediction models for anxiety and depression were found in a US study among undergraduate students using ML techniques(36). This study also used EHR information, and only included biomedical and demographic information, on purpose excluding any psychiatric information(36).

However, it also means that such a prediction model cannot be used with a cut-off value above which children are labelled to have problems. The models should be seen more as a tool to give insight in the factors that are found to be predictive for MHPs. Given the above, it is advocated that early identification of MHPs with screening tools or predictive algorithms cannot stand alone and that emphasis should be placed on research regarding the ability of screening instruments to improve clinical decision-making(37).

Automatic pop-up indicating a child's vulnerability to developing MHPs

We believe that a prediction model could aid physicians in daily clinical practice to identify children like Tess at risk of developing MHPs. Such a model could be translated into an automatic pop-up in a child's EHR to alert the GP when the child comes in for

a visit. The pop-up would show the vulnerability of a child to develop MHPs in, for instance, the next year. The GP could then take this vulnerability into account during the consultation. We see the pop-up as a tool to support GPs, which should always be used next to the clinical judgement of the physician, and the wishes of both the child and the parents. Especially as the recognition of child MHPs differs from the recognition of somatic diseases, as outlined above.
A similar concept can be found in geriatrics, where electronic frailty indexes based on primary care EHR information are currently being evaluated(38).

The aim of an automatic pop-up in the child's EHR could be viewed in the same way: early identification of children at risk of developing MHPs to improve informed, shared decision-making, allowing physicians to tailor interventions to their patients' individual needs and prevent adverse outcomes in later life(39). Ideally, the pop-up would already be based on combined information from general practice and PYH. But when the pop-up would only be based on information from the general practice EHR, the GP could actively assess information from PYH (e.g. regarding mental health screening tools) in case the pop-up would indicate a child being vulnerable and incorporate this knowledge in the clinical decision-making process.

How do our findings improve the early identification of child MHPs?

This thesis provides further evidence that there is a substantial inter-professional variation in the identification of child MHPs in primary care. Although the prediction models we developed did not perform well enough yet to support GPs in daily practice, the results of this thesis can still help professionals to improve the early identification of child MHPs.

First, knowledge about (a combination of) the individual risk factors for child MHPs based on general practice data could support GPs in the identification of child MHPs. These risk factors include amongst others somatic complaints and healthcare use-related risk factors. In addition, this thesis shows that information from PYH regarding results from mental health screening tools, concerns for MHPs, exposure to life events, family history of MHPs and an extra visit in PYH could be relevant to share with general practice. Especially as some of these characteristics were also predictive for the group of children that was registered as having used child and adolescent mental healthcare (CAMH), but that was not registered as having MHPs according to GPs (chapter 6).

Although the scenario of an automated pop-up is still a long way off – as described earlier, there are still barriers to resolve further – this thesis shows what could be done in the meantime to help children like Tess in an earlier stage: namely, improving collaboration and information exchange between general practice and PYH.

We believe that a structured exchange between PYH and general practice of some of these relevant key elements would support GPs in the early identification of child MHPs and in treating children like Tess. Better information exchange between PYH and general practice was also mentioned as the most important point for improvement of the collaboration in general by the participating GPs and PYHPs in our qualitative study. We feel that exploring the structural exchange of some characteristics registered in PYH that are relatively easy to obtain, exchange and interpret, such as scores of mental health screening tools, PYH concerns for MHPs and school problems, might be a good starting point for improving collaboration, and, more importantly, improving the early identification of child MHPs.

Proactive, integrative care for children at high risk

Structural information exchange between GPs and PYHPs could improve the early identification of child MHPs. Early identification is important in order to provide adequate treatment strategies and enable prevention of adverse outcomes in later life(40). The scenario of an automatic pop-up that indicates the vulnerability of a child to develop MHPs, or in an earlier stage structural information exchange of some relevant information between general practice an PYH, would provide an efficient solution to support GPs. This is particularly interesting since the majority of GPs nowadays work part time and fewer GPs want to become practice owners(41), potentially resulting in the loss of important knowledge regarding the context of patients and less continuity of care. These factors can hamper MHP identification.

In addition, the duties of GPs have changed over the years. An increased burden of administrative duties, growing possibilities for diagnostics and management, system changes such as in the care for youth ('Transitie Jeugdzorg'), elderly and in mental healthcare, and substitution of care from secondary to primary care all result in more complex problems GPs have to face(41). In light of this, the main tasks and values of general practice were redefined in 2019. Next to providing general medical care, emergency care and terminal palliative care, prevention and coordination were defined as core tasks of Dutch general practice(41). Not only are GPs responsible for the care provided by their own team, they are often also the

connecting factor between and the first point of contact for other care providers who have medical questions about their patients(41). Adequate information exchange between healthcare providers therefore is essential.

The GP core tasks coordination and prevention also fit in with a panel management approach, which is a form of population health management, and the increasing political attention for prevention in healthcare. In panel management, a set of tools and processes for population care are applied systematically on populations at a defined risk with physicians directing proactive care for those high-risk patients(39). This is to enable adequate, efficient, patient-centred care and to minimize care waste. The early identification of children like Tess who are at high risk of developing MHPs can be seen as the first step of panel management. Multidisciplinary collaboration and information exchange between general practice and PYH would have beneficial effects for the proactive identification and management of these children.

Additional recommendations for future research

In addition to previously mentioned recommendations for future research, we have outlined several other recommendations below. First, the work presented in this thesis suggests that better information exchange between general practice and PYH is both desirable and useful. Exploring the structural exchange of some characteristics registered in PYH that are relatively easy to obtain, exchange and interpret, such as scores of mental health screening tools, PYH concerns for MHPs and school problems, can be a good starting point. We recommend future studies to investigate whether this information exchange is indeed desired and how structural information exchange can be executed in a practical manner. Factors such as privacy and patients' consent for information exchange should be taken into consideration.

We found that a small group of children was registered as having used CAMH, but was not registered as having MHPs according to GPs. We would recommend further investigation into these children: who are they and how did they end up in CAMH? What can we learn from their non-standard entry to the CAMH system? Data from CAMH referral letters or information from the social domain including 'jeugdteams' or 'wijkteams' might be helpful.

When a better performing prediction model to aid child MHP identification can be developed, it should be investigated whether such model improves the identification of the right children, i.e. children who actually have MHPs. In addition, one should

pay attention to children who never visit a GP. These children are less likely to have information registered in their EHR and so less likely to be identified as at high risk of developing MHPs.

We also found that registered somatic complaints (e.g. headache or constipation) were a predictor for MHPs registered by GPs. We would suggest a closer look is taken at children with somatic complaints. Factors like the course of the somatic symptoms, including accompanying diagnoses, number of visits and referrals to secondary care should be explored. A long-term follow-up of these children into adulthood would be also very interesting. Is there a relationship between a patient having registered medically unexplained physical symptoms in adulthood or being a frequent healthcare user? And from a family perspective, how is the healthcare use and occurrence of MHP diagnoses and potential medically unexplained physical symptoms in the parents of these children?

Conclusion

MHPs are common in children and adolescents. This thesis provides further evidence that the prevalence rates of MHPs identified by primary care professionals varied substantially and that many of the children with an increased risk of MHPs are not identified as such. This thesis shows that GPs can be supported in their early recognition and referral decisions concerning MHPs in children with the results of thorough analysis of routine healthcare data. In addition, further improvement of registration and data-reusability would enable further improvement of primary healthcare for children with MHPs. This thesis also reveals that it is useful to share information between general practice and PYH, and that there is a wish for improved information exchange and collaboration between general practice and PYH. Based on the findings of this thesis we believe that the information exchange between PYH and general practice should be strengthened.

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