Machine learning methods applied on dental fear and behavior management problems in children

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The etiologies of dental fear and dental behavior management problems in children were investigated in a database of information on 2,257 Swedish children 4–6 and 9–11 years old. The analyses were performed using computerized inductive techniques within the field of artificial intelligence. The database held information regarding dental fear levels and behavior management problems, which were defined as outcomes, i.e. dependent variables. The attributes, i.e. independent variables, included data on dental health and dental treatments, information about parental dental fear, general anxiety, socioeconomic variables, etc. The data contained both numerical and discrete variables. The analyses were performed using an inductive analysis program (XpertRule Analyser®, Attar Software Ltd, Lancashire, UK) that presents the results in a hierarchic diagram called a knowledge tree. The importance of the different attributes is represented by their position in this diagram. The results show that inductive methods are well suited for analyzing multifactorial and complex relationships in large data sets, and are thus a useful complement to multivariate statistical techniques. The knowledge trees for the two outcomes, dental fear and behavior management problems, were very different from each other, suggesting that the two phenomena are not equivalent. Dental fear was found to be more related to non-dental variables, whereas dental behavior management problems seemed connected to dental variables. □ *Artificial intelligence; behavioral dental science; dental anxiety; etiology; pedodontics*

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Data files contain information characterized by a mixture of discrete and numeric variables which can represent information overload or clusters unless relationships and patterns in the data can be derived. Statistical analysis methods may to some extent elucidate the inborn knowledge. The objective of gaining information and learning from knowledge in data files is to render the knowledge explicit.

Machine learning methods such as inductive learning, neural nets, and evolving rules in which genetic algorithms and other methods within the field of artificial intelligence have been used have rapidly developed for use in personal computers and become powerful methods (1–11).

Artificial intelligence is concerned with methods for automatic learning where inductive learning is one method used for knowledge acquisition. A database of examples is used to generate rules automatically, and the derived rules are normally presented in symbolic descriptions semantically and structurally similar to those a human expert might produce observing the same examples. The aim of the induction is to find a set of rules by which the relationships between the variables are revealed through information (examples). The inductive system can handle large data sets and complex problems with different types of relations and will quickly find rules that are not apparent to people. The output is usually a set of rules graphically displayed as a knowledge tree that renders the knowledge transparent. The inductive approach is therefore suitable as a tool in research and development.

Dental fear and dental behavior management problems (BMP) are common occurrences in child dental care. Swedish population-based studies have shown prevalence figures of up to 10% (12–14). There are differences between dental fear and anxiety (DFA), on the one hand, and dental BMP on the other. Dental fear concerns the child's experience, while BMP is the uncooperative behavior noted by the treating dentist (15). Both dental fear and BMP are of multifactorial origin (see, e.g., 15, 16). The etiologies of DFA and BMP have mainly been investigated by using bivariate statistics and a range of multiple regression analyses. However, since the relationships are complex there is a need for additional analyzing techniques to better understand causality.

The aim of this study was to test the usefulness of computerized inductive techniques within the field of artificial intelligence on a database containing information on dental fear and BMP problems in children, and data concerning dental health and treatment compiled from dental records. In addition, utilizing the inductive technique we analyze the background factors of DFA and BMP.

Material and methods

Patient material and data information

The eligible patient material consisted of 3,204 children

Table 1. Variables used in analyses

Variable	Explanation	Abbreviation
CFSS-DS	Dental Subscale of Children's Fear Survey Schedule Measures dental fear; scores ≥ 38 indicates dental fear; scores ≥18 = no fear	CFSS-DS
Age	Young = 4–6-year-olds Old = 9–11-year-olds	Age
Gender	Boys and girls	Gender
Clinic	Low = area with low SES; 2 clinics Medium = area with average SES; 1 clinic High = area with high SES; 2 clinics	Clinic
Father's occupation	Low = skilled, unskilled workers Medium = small-scale employers, officials of lower rank High = large-scale employers, officials of high or intermediate rank	F-OCC
CFSS-SF	Short Form of Children's Fear Survey Schedule Measures general anxiety Low = 18–25 Medium = 26–46 High = 47–90	CFSS-SF
DAS-M	Dental Anxiety Scale; used in mothers Measures dental fear in adults Low = 4–5 Medium = 6–14 High = 15–20	DAS-M
DAS-F	Dental Anxiety Scale; used in fathers Measures dental fear in adults Low = 4–5 Medium = 6–14 High = 15–20	DAS-F
Fear of going	Parents' answer to question in questionnaire If the child had shown fear of going to the dentist Yes/No	Q.FEAR
Uncooperative Behavior	Parents' answer to question in questionnaire If there had been difficulties in carrying out treatment Yes/No	Q.BMP
Caries	Numbers of carious tooth surfaces according to dental records No cavities = 0, Few = 1–4, Many = 5–8, Extreme ≥ 9	NO.CARIES
Fillings	Numbers of filled tooth surfaces according to dental records No fill = 0, Few = 1–4, Many = 5–16, Extreme ≥ 17	NO.FILLED
Dental trauma	Parents' answer to question in questionnaire If the child has had trauma injuries to the teeth Yes/No	Q.TRAUMA
Language	Native language Swedish/Nordic/Non-Nordic	LANGUAGE
Restorations	Parents' answer to question in questionnaire If the child has had filling therapy Yes/No	Q.RESTOR
Injection	Parents' answer to question in questionnaire If the child has experienced dental local anesthesia Yes/No	Q.INJ
Behavior management problems	Dental behavior management problems according to dental records BMP/Non-BMP	BMP
Painful treatment	Experiences of filling therapy without use of local anesthesia according to dental records	NON.LA
Missed appointments	Numbers of missed appointments according to dental records	NO.MISSED
Appointments	Numbers of appointments according to dental records Missed = 0, Few = 1–2, Medium = 3–5, many ≥6	NO.APP
Frequency BMP	Numbers of appointments with dental behavior management problems None = 0, Few = 1, 2 + ≥ 2	NO.BMP

(1,550 boys and 1,654 girls) aged 4–6 and 9–11 years of age. This group had previously been surveyed in regard to dental fear and anxiety using questionnaires and psychometric measures. The children had been selected in order to mirror the total child population of the City of Göteborg concerning geography and socio-economics. The dental records were retrieved from the Public Dental Service in Göteborg and dental records matching the period when the questionnaires were sent out were found for 2,974 of the children. A total of 21 variables from both questionnaires and dental records were identified for the present investigation. Information on all 21 variables was set as a criterion for inclusion in the study, and 2,257 children met this.

All variables included in the study are given in Table 1. A psychometric measure from the questionnaire—Dental Subscale of Children's Fear Survey Schedule (CFSS-DS) (17)—was used to define dental fear. This test contains 15 items with a Lickert-type response format and with a possible sum score ranging from 15 to 75. Scores equal to or exceeding 38 have been shown to indicate dental anxiety, and scores of 18 or less no anxiety (18). Dental BMPs were defined as notes in the dental records clearly expressing uncooperative/disruptive behavior resulting in major delay in treatment or rendering treatment impossible. The CFSS-DS and BMP were both used as outcomes in the analyses.

The questionnaire provided information about parental dental fear and general anxiety/emotional status and contained several direct questions about experiences from dental care (Table 1). The Dental Anxiety Scale (DAS) (19) measures fear in adults and has a possible score range of 4 to 20. Scores of 15 or more indicate high dental anxiety, whereas scores of 4 or 5 are considered to be low (20, 21). A constructed Short Form of Children's Fear Survey Schedule (CFSS-SF) derived from the original scale by Scherer & Nakamura (22) was used to assess general fear in the children. The Short Form has a score ranging from 18 to 90. Based on data from Swedish children, scores of 47 or more were considered as high and scores of 25 or less as low (13).

Information about dental treatments and dental health was obtained from the dental records. This has previously been described in detail (14).

Computerized analysis

Preparation of data

The answers in the questionnaires were numerically coded and processed using a computerized spreadsheet program (Excel® 5.0, Microsoft) to generate an ASCII file format. The analyses were performed using an inductive analysis program XpertRule Analyser (XpertRule Analyser®, Attar Software Ltd, Lancashire, UK). The methodology has been presented in detail in a previous publication (23), which is why only a short description is given here. The results are presented in a hierarchic diagram in which the importance for every specific variable (originally independent variables), called attribute in inductive analyses, is specified by its position and level in the knowledge tree; the higher in the tree the more important for the outcome (originally dependent variable). A tree, thus, shows how different attributes affect other attributes.

After import to the XpertRule Analyser® the set of data, representing attributes with different values, was assigned as either discrete or numeric attributes. Some of the values for certain attributes were further grouped in order to limit the number of discrete values and improve the analyses. For rule induction the selected outcome has to be discrete. As the chosen outcome contains a large number of values it is necessary to focus on only a limited number, thus enhancing understanding and the possibility of interpreting the resulting knowledge trees or pattern rules. The grouping for both the attributes and the outcome was based on knowledge of the data file and is presented in Table 1.

In the XpertRule Analyser® the Rank option ranks the attributes in accordance with their effect on the outcome, thus enabling a narrowing down of the selection of attributes. After defining the outcome, and the grouping procedure had been carried out, ranking of the attributes was performed.

Induction process

Rule Induction is the process of producing a generalized knowledge tree from a data set. The knowledge tree is generated by repeatedly (recursively) splitting the given data set according to different attributes until terminal points (leaves) are reached. The order by which the attributes are used in the knowledge tree depends on a measure of the classification power of each attribute.

Pruning

Pruning is used to reduce the effects of noise in the induced knowledge tree. The effects of noise, insufficient attributes, and insufficient data manifest themselves as excessive branches localized near the leaves of the tree away from the root. This localization presents the opportunity to remove these effects by effective pruning of the tree.

Verifying process

The accuracy of the pruned knowledge tree can be validated against the test data set, which is a portion of the development data automatically set aside by the Analyser®. The program randomly selects 50% of the data for induction of rules (training), while the remaining 50% is used in the verifying process (test). The Verify option displays a table showing the accuracy (predictability) of each leaf by comparing the probabilities of the leaf outcome in the training and testing data sets. This is expressed as percentage correctly classified. For each leaf, the table also compares the percentages of the training and test data that fall into that leaf.

Normalization of data

Normalization may be needed to correct for imbalance in the frequency of occurrence of outcome groups in the data set. In the present study we chose to make a proportionally larger sample of rarer outcomes to be included in the tree development data sample. This is

Table 2. Ranking of attributes, use of attributes. Outcome = CFSS-DS; with values low = 15–18; medium 19–37; high ≥ 38. Number of patients = 2257

Variable	Usage	Rank	1% prune leaf node	0.1% prune leaf node
CFSS-SF	Attribute	1	1	1
NO. BMP	Attribute	2	5	5
BMP	Attribute	3	2	2
DAS-M	Attribute	4	3	3
AGE	Attribute	5	4	5
DAS-F	Attribute	6	4	4
LANGUAGE	Attribute	7	6	6
NO.FILLED	Attribute	8	3	3
F-OCC	Attribute	9	8	8
CLINIC	Attribute	10	3	3

Correctly classified % training/test	No prune	1% prune	0.1% prune
Low	74.8/58.2	65.1/59.5	62.5/59.8
Medium	56.0/44.1	40.1/33.6	29.8/25.5
High	92.2/31.7	82.8/56.6	89.1/66.7
Overall	74.6/44.9	62.9/49.8	60.8/50.5
No. of leaves	250	38	30

Excluded: GENDER, NO.CARIES, NON.LA, NO.MISSED, NO.APP, Q FEAR, Q BMP, Q TRAUMA, Q RESTOR, Q INJ.

taken into account when interpreting the knowledge tree patterns. The process of correcting for imbalance in the data is called frequency normalization and a multiplier is set for each outcome value. The probability and size figures at each leaf take these multipliers into account, as does validation and the setting of outcome leaves.

Definition of outcome attributes and values

After importing the data to the Analyser® the outcomes were set to fields related to DFA and BMP. The values of the outcomes were then grouped into three and two groups, respectively; for DFA according to limits determining if the patient exhibited a LOW (≤18), MEDIUM (19–31,37) or HIGH degree (≥38) of DFA, and for BMP according to whether the dental records reported uncooperative behaviors delaying treatment/rendering treatment impossible or not (BMP vs. NON-BMP).

The analyses were performed in the following way: All attributes, including the 10 with the highest ranking, were used for the analysis of the two different outcomes. As this analysis proved seriously biased and with too much noise by some of the attributes it was decided to exclude these attributes from further analysis.

The following attributes were thus excluded in the analyses holding CFSS-DS as outcome: Q.FEAR, Q.BMP, Q.TRAUMA, Q.RESTOR, Q.INJ. In the analyses in which BMP was used as outcome the previous attributes and NO.BMP were excluded.

The complete material, using the remaining sets of attributes, was analyzed in three different ways: All patients ($n = 2257$), young age group ($n = 1119$), and old age group ($n = 1138$). In the analyses of the two age groups (young and old) the attribute AGE was also excluded.

After ranking, the 10 highest ranked attributes were used in the analyses. Pruning was carried out at the 1% and 0.1% levels. Validations of the analyses were performed after the initial induction as well as after pruning.

Results

Analyses for dental fear—CFSS-DS

The ranking, used attributes, location of attributes in the different knowledge trees, and the percentage correctly classified outcome values in the training and test sets are given in Tables 2–4. The nodes are only given in tables when the corresponding trees hold less than 40 leaves. As the knowledge trees are extensive, it was decided to omit from the paper any that were not ideal for presentation; however, these are available on request from the authors. Concerning CFSS-DS it could be seen from the tree that general fear (CFSS-SF) and dental fear of the mother (DAS-M) were the most important attributes according to their positions in the knowledge tree.

The knowledge trees for young and old children with CFSS-DS as outcome differed from each other. In the young group, BMP combined with few or no cavities were associated with high levels of dental fear. For older children the tree was more complex and general fear was found in the first node.

Analyses for BMP

The ranking, used attributes, location of attributes in the different knowledge trees and the percentage correctly classified outcome values in the training and test sets are given in Tables 5–7. The nodes are only given in tables when the corresponding trees hold less than 40 leaves. Important variables in the knowledge tree with BMP as outcome were general fear and socio-economic factors located at high levels; low age was also a discriminating variable. For the same reasons as stated above, these trees too were omitted from publication.

Comparing the two age groups with BMP as outcome also showed differences between younger and older children. In the younger group, higher numbers of appointments were associated with BMP, whereas the tree in the older group had numbers of carious surfaces located highest. The latter tree was, again, more complex.

Comparisons between BMP and CFSS-DS

The knowledge trees with CFSS-DS as outcome appeared to be more connected to non-dental variables and variables such as general anxiety, and parental dental fear appeared to be more important. BMP, on the other

Table 3. Ranking of attributes, use of attributes. Outcome = CFSS-DS; with values low = 15–18; medium 19–37; high ≥ 38. Number of patients = 1119. Young age group (4–6-year-olds)

Variable	Use	Rank	1% prune leaf node	0.1% prune leaf node
NO. BMP	Attribute	1	1	1
BMP	Attribute	2		
CFSS-SF	Attribute	3	2	2
DAS-F	Attribute	4		
DAS-M	Attribute	5	3	3
LANGUAGE	Attribute	6	6	6
NO.CARIES	Attribute	7	2	2
NO.APP	Attribute	8	5	5
NO.FILLED	Attribute	9	6	
F-OCC	Attribute	10	5	5
Correctly classified % training/test		No prune	1% prune	0.1% prune
Low		67.4/51.9	83.9/79.2	83.9/79.2
Medium		65.6/54.7	31.2/27.4	32.9/29.4
High		77.8/22.9	51.1/37.4	44.4/33.4
Overall		70.2/43.0	55.4/47.9	53.9/47.2
No. of leaves		107	12	10

Excluded: AGE, CLINIC, GENDER, NON.LA, NO.MISSED, Q FEAR, Q BMP, Q TRAUMA, Q RESTOR, Q INJ.

Table 4. Ranking of attributes, use of attributes. Outcome = CFSS-DS; with values low = 15–18; medium 19–37; high ≥ 38. Number of patients = 1138. Old age group (9–11-year-olds)

Variable	Use	Rank	1% prune leaf node	0.1% prune leaf node
CFSS-SF	Attribute	1	1	1
DAS-M	Attribute	2	3	4
BMP	Attribute	3	4	3
NO.BMP	Attribute	4	3	3
LANGUAGE	Attribute	5	2	5
NO.FILLED	Attribute	6	6	7
CLINIC	Attribute	7	4	
DAS-F	Attribute	8	3	5
NO.CARIES	Attribute	9	5	4
F-OCC	Attribute	10	5	8
Correctly classified % training/test		No prune	1% prune	0.1% prune
Low		85.0/68.2	64.7/69.2	65.4/57.1
Medium		72.7/48.1	63.0/57.1	65.6/60.1
High		100.0/23.4	100.0/23.4	100.0/37.4
Overall		85.4/45.8	75.1/49.1	76.8/51.4
No. of leaves		144	17	16

Excluded: AGE, GENDER, NON.LA, NO.MISSED, NO.APP, Q FEAR, Q BMP, Q TRAUMA, Q RESTOR, Q INJ.

hand, appeared to be more connected to dental-related variables such as number of appointments, number of cavities, and also some social factors.

Discussion

This study has demonstrated that inductive techniques are useful when analyzing complex relationships in large data sets. There are two modes of learning—supervised and unsupervised learning. Unsupervised learning can be used to discover any clustering or patterns in data without specifying an outcome data field of interest. Supervised learning is used to generate rules and patterns linking a selected data field to other designated data fields. The Analyser® is a tool for supervised symbolic learning that supports rule induction (23). The overall objective of using an inductive tool for the analysis of data is to derive knowledge trees from data files (8, 24, 25, 26). The Analyser® can operate on a file from which a graphical knowledge tree is generated to profile any data field in relation to other data fields. Learning from data can thus be considered an alternative knowledge engineering strategy if the data represent records of expert decision-making.

Inductive methods are complements to more traditional

Table 5. Ranking of attributes, use of attributes. Outcome = BMP; with values BMP, Non BMP. Number of patients = 2257

Variable	Use	Rank	0.1% prune leaf node
CFSS-DS	Attribute	1	1
NO. CARIES	Attribute	2	2
AGE	Attribute	3	3
F-OCC	Attribute	4	3
NON.LA	Attribute	5	4
NO.MISSED	Attribute	6	6
LANGUAGE	Attribute	7	4
CLINIC	Attribute	8	2
CFSS-SF	Attribute	9	5
DAS-F	Attribute	10	6
Correctly classified % training/test	**No prune**	**1% prune**	**0.1% prune**
BMP	93.4/35.9	83.5/53.3	80.2/58.7
Non-BMP	89.3/83.6	84.1/79.6	82.5/79.6
Overall	91.3/59.7	83.8/66.4	81.4/69.1
No. of leaves	131	53	36

Excluded: GENDER, DAS-M, NO.FILLED, NO.APP, NO.BMP, Q FEAR, Q BMP, Q TRAUMA, Q RESTOR, Q INJ.

Table 6. Ranking of attributes, use of attributes. Outcome = BMP; with values BMP, Non BMP. Number of patients = 1119. Young age group (4–6-year-olds)

Variable	Use	Rank	1% prune leaf node	0.1% prune leaf node
NO.APP	Attribute	1	1	1
NO. CARIES	Attribute	2	3	3
CFSS-DS	Attribute	3	2	2
NON.LA	Attribute	4	4	4
NO.MISSED	Attribute	5	5	
NO.FILLED	Attribute	6	8	
F-OCC	Attribute	7	3	3
LANGUAGE	Attribute	8		
CLINIC	Attribute	9	3	3
DAS-F	Attribute	10	3	4
Correctly classified % training/test		**No prune**	**1% prune**	**0.1% prune**
BMP		93.7/55.4	90.7/67.7	84.6/72.3
Non-BMP		90.5/83.4	84.4/79.8	83.0/77.4
Overall		92.1/69.4	87.6/73.7	83.8/74.8
No. of leaves		69	27	14

Excluded: AGE, GENDER, CFSS-SF, DAS-M, NO.BMP, Q FEAR, Q BMP, Q TRAUMA, Q RESTOR, Q INJ.

statistical methods and it has to be borne in mind that in order to understand which variables have to be used in relation to a specific outcome it is essential to have knowledge about the data to be analyzed. The use of knowledge trees allows relationships to be made explicit and understandable. Each outcome can readily be followed to the end node and thus be validated. Furthermore, the different attributes and their positions in the knowledge trees mark their importance in relation to the outcome.

Grouping of the data, for example grouping of the numeric values for age into 2 age groups, Young and Old, may improve the analysis considerably. This is especially relevant when an attribute consists of a larger number of values (32 being the limit of the system) and the number of examples is less than 2,000.

When an imbalance in the frequency of outcome groups occurs due to there being a proportionally larger sample of rare outcomes to be included in the tree, the total number of available records for various outcome groups has to be assessed.

Regardless of the reason for having a development set with a disproportionate percentage of the total available records for various outcome groups, this must be considered when interpreting the decision tree patterns. The first step is to correct the probability figures shown on the leaf by taking into account the actual proportion of various outcome groups in the data. If for example there

Table 7. Ranking of attributes, use of attributes. Outcome = BMP; with values BMP, Non BMP. Number of patients = 1138. Old age group (9–11-year-olds)

Variable	Use	Rank	1% prune leaf node	0.1% prune leaf node
CFSS-DS	Attribute	1	2	2
NO. CARIES	Attribute	2	1	1
NO.APP	Attribute	3	3	3
CFSS-SF	Attribute	4	8	8
CLINIC	Attribute	5	5	5
F-OCC	Attribute	6	6	9
LANGUAGE	Attribute	7	4	4
DAS-F	Attribute	8	6	6
DAS-M	Attribute	9	8	
NO.FILLED	Attribute	10	2	2
Correctly classified % training/test		No prune	1% prune	0.1% prune
BMP		100.0/25.9	100.0/44.5	100.0/51.9
Non-BMP		93.7/90.1	86.2/80.3	83.6/77.7
Overall		96.8/57.7	93.0/80.3	91.7/64.7
No. of leaves		55	28	23

Excluded: AGE, GENDER, NON.LA, NO.MISSED, NO.BMP, Q FEAR, Q BMP, Q TRAUMA, Q RESTOR, Q INJ.

are 2 outcome groups in a leaf with M and N data records, then the probability figure shown on the leaf (assuming that $M > N$) is $M/(M + N)$. If the ratio of outcome group 1 to outcome group 2 in the development sample is F times smaller than that in the normal data as a whole then the corrected probability figure is $F*M/(F*M + N)$. The process of correcting for the imbalance in the data is called frequency normalization and was used in this study to correct the imbalance in the number of patients with dental fear. The probability and size figures at each leaf take these multipliers into account, as does validation and the setting of outcome leafs.

The term Noise, when applied to data files, can mean a number of things. It can mean that the data fields are corrupted due to typing errors or transmission errors and/or the data fields contain inaccurate information as a result of human errors in decision-making or machine errors in logging events. This is also valid in cases when the data file does not contain enough data or sufficient numbers of attributes to cover the patterns we are trying to discover and/or classify the outcome field, as well as when the file contains attribute fields, which are irrelevant to the classification of the outcome field (27).

Localization of the effects of noise near the leaves presents an opportunity to remove these effects by effective pruning. Pruning the tree will simplify matters to the extent that it no longer classifies all the records of the sample. Nevertheless, the pruned tree contains valuable information that is easy to understand and interpret (27). As the inductive methodology has the potential to expose which attributes are redundant, a new analysis can be carried out using only relevant attributes and values.

In this study, the knowledge trees became extensive sometimes even after pruning. It is thus evident that the data files do not contain enough information to correctly classify the different outcomes or that the relationships are so complex that known methods in knowledge acquisition within the fields of this study are not sufficient.

The knowledge trees for the two outcomes CFSS-DS and BMP look very different from each other, which emphasizes the theory that BMP is not equal to dental fear or anxiety previously discussed by Klingberg et al. (15). However, it can be concluded from the CFSS-DS tree that general fear (CFSS-SF) and dental fear of the mother (DAS-M) are the most important explanatory variables, which strengthens the theory that there is a strong connection between general fear and fear of the mother (29,30).

When the different age groups were analyzed with CFSS-DS as outcome, the influence of age became evident, which obviously can be explained by the differences in cognitive development and emotional maturity in young and older children. General anxiety was an important factor for both age groups, but more so in the older children. Younger children run a higher risk of developing dental fear if they are uncooperative during dental treatment and have few carious lesions. The reason for these children having BMP is not known. It could reflect an anxiety of the unknown as they had had limited experience of dental treatment, illustrated by the fact that numbers of filled surfaces did not enter into the analysis in the young age group as they did for older children and for the total study group. Previous studies have shown that positive experiences from restorative treatments, i.e. pain-free, can lead to a decrease in levels of dental fear and anxiety (13, 29), and that children actually experience less discomfort during treatment (injection, drilling, and filling) than they had expected (31). The analyses and knowledge trees for the total group and for the older group include numbers of filled surfaces, which can be interpreted as experience of dental treatment. The results in these parts are contradictory, as high numbers of filled surfaces are sometimes linked to high levels of dental fear, and inversely the no previously filled surfaces situation is sometimes associated with high dental anxiety. A possible explanation could be that the modes of treatment, experienced discomfort or pain during treatment, are not fully known in this context.

When BMP is the outcome there are still differences to be seen between the younger and older age groups. CFSS-DS can be explained by the influence of normal development. The young child is neither used to, nor comfortable with, the dental situation, which is reflected in the knowledge tree as number of appointments, i.e. the highest position. This is reasonable, as the more visits the higher the risk for developing BMP. Furthermore, a child noted for several appointments is also very likely to have an extended need for restorative dental treatment, which increases the risk of stressing and unpleasant experiences. For the older children the attribute number of carious surfaces is at the first node and it is thus evident that children exhibiting BMP appear to have a lot of caries, dental fear, and have experienced restorative treatment.

When BMP is compared with dental fear within the 2 age groups, as well as for the total group, it appears that CFSS-DS is connected more with non-dental variables, such as internal variables and external variables of the immediate environment of the child, i.e. its own general anxiety as well as parental dental fear. The assumption that BMP is connected with dental variables is supported by the findings in the knowledge trees. Prospective studies need to be carried out if we are to better understand the differences between DFA and BMP. The present investigation has demonstrated that inductive techniques can be very useful in this work. Prospective studies could also include evaluation of treatments and preventive action against DFA/BMP.

Even though the different knowledge trees were complex in their structure the inductive technique is useful for showing complex relations. However, the method must be combined with more traditional statistical methods of analysis. An interesting feature of Analyser® is that since redundant variables are omitted from the knowledge tree, the analysis can be carried out focusing on the impact of the outcome from more relevant variables. Furthermore, it is also evident when variables are missing. The hierarchic structure of the knowledge trees makes them relatively easy to interpret and validate. In prospective studies, economic variables can be attached to the system and thus qualitative data evaluated economically.

Concluding remarks

Inductive techniques are useful complements when analyzing complex relationships. The analyses of the 2 outcomes, dental fear and BMP, showed that the 2 phenomena are not equivalent and that they are of different etiology. Dental fear was found to be more related to non-dental variables, whereas dental BMP seemed connected to dental variables.

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