

Anterior Crossbite Treatment Made Simpler-with Glass Ionomer Cement Blocks.

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Abstract

Anterior crossbites are often encountered in orthodontic practice. One or more teeth may be affected, and the etiology can be dental, skeletal or dento-skeletal.

Crossbites of dental origin affect only some of the teeth in an area of the arch, and are less severe than crossbites due to jaw discrepancies but occlusal interferences often are present, increasing the chances of a shift on closure.

Correction of dental crossbites in the mixed dentition is recommended because it eliminates functional shifts and wears on the erupted permanent teeth and possibly dentoalveolar asymmetry.

This usually also increases arch circumference and provides more room for the permanent teeth. An untreated anterior crossbite may cause periodontal problems, while reports state that the mandible may grow disproportionality.

Relapse into crossbite is unlikely in the absence of a skeletal problem, so early correction also simplifies future treatment by eliminating the problem from the list.

Orthodontists have an armamentarium of devices, including removable appliances, expanders, fixed appliance and orthopaedic appliances such as the facemask for correcting the anterior crossbite.

Despite the variety of the aforementioned appliances, treating an anterior crossbite early, can be a challenge.

We will discuss the effect of a simple, inexpensive and patient friendly approach we have found to work consistently well. At the same time, we will examine physiological changes that lead to successful treatment.

What can be better than allowing natural forces to play their role rather than going for complex mechanical devices to correct a malocclusion!

Introduction

Anterior crossbite is defined as a malocclusion resulting from the lingual position of the maxillary anterior teeth in

relationship with the mandibular anterior teeth¹. Anterior crossbites are often encountered in orthodontic practice. One or more teeth may be affected and the etiology can be dental, skeletal or dento-skeletal².

This type of malocclusion is represented in 27% of the transverse and vertical malocclusions noticed³. A variety of factors have been reported to cause a dental anterior crossbite, including a lingual eruption path of the maxillary anterior teeth, trauma to the deciduous dentition in which there is displacement of the tooth buds, delayed eruption of the deciduous dentition, supernumerary teeth, and inadequate arch length^{4,5}.

Early treatment is directed towards preventing dysplastic growth of both the skeletal and the dentoalveolar components. In addition, it prevents excessive, abnormal wear of the labial surfaces of the maxillary incisors and the incisal edges of both the maxillary and the mandibular incisors. It avoids the risk of periodontal problems in the mandibular incisors because of traumatic forces that become higher as the muscles of mastication become stronger with age and the bite deepens⁶. Early treatment also alleviates functional posterior crossbites that can develop as a result of tooth interferences and incorrect occlusion⁷. Since crossbites are seldom self-correcting, because of the relationship of the permanent to primary predecessors, early treatment can re-establish proper muscle balance, and thus preventing adjustment of the jaw muscles on the position resulting from the habitual posturing of the mandible.

Differential diagnosis of dental versus skeletal anterior crossbite is essential in the selection of cases that can be treated. To differentiate dental from skeletal crossbite, one should attempt to guide the mandible in centric relation and evaluate the molar and incisor relationship, as well as estimate the relative size of the mandible compared with the maxilla. If the molars are in a class I relationship and the incisors at an end to end relationship, a dental correction can be

undertaken.

Selection of the appliance for correction of the crossbite is essential for successful treatment. The appliances suggested in the literature for correction of anterior crossbites in mixed dentition can be in the form of mandibular acrylic inclined planes, reverse stainless steel crowns, tongue blade therapy, removable plate with screws or auxiliary springs or fixed light archwires^{8,9}.

The force exerted by appliances like acrylic inclined planes, tongue blade therapy etc. is dependent on the chewing action of the patient and therefore is unpredictable. Furthermore, the heavy forces exerted can traumatize the teeth. In addition, although easily accepted, stainless steel crowns are quite unesthetic¹⁰. The patient's compliance is essential for successful treatment, especially in the young child and may resist any kind of treatment. Elimination of this factor favours the use of fixed appliances. Myers¹¹ found that poor patient cooperation resulted in discontinuation of 12% of the removable appliances but only 4% of the fixed appliances. Also, 12% of the removable appliances were lost compared with only 1% of the fixed appliances.

The technique discussed here is a simple, inexpensive, and patient friendly approach we have found to work consistently well; by the action of physiological forces which led to the successful results without the use of any form of external forces.

Method And Materials

The method consists of bilaterally building the occlusal surfaces of mandibular deciduous and permanent first molars with coloured glass ionomer cement (Ultradendok) this cement is known for its strength and ability to release fluoride and due to its blue colour, it is easily distinguishable from the tooth surface to facilitate its sequential trimming and removal. There is no need to etch or prime the teeth before applying the cement and the clinician can easily equilibrate the two

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