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EDITORIAL

Lessons we have learned from osseointegration can guide us when using artificial intelligence

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Once P-I Brånemark introduced the concept of osseointegration in 1982 at the Toronto Conference with his tissue-integrated prosthesis[1] to restore the mandibular complete denture "amputee," implant restorative modalities for the partially edentulous patient followed. Beginning in the 1990s and spanning the next 3 decades, many in vitro studies were conducted to assess the relative stress distribution of various prosthetic designs to the peri-implant bone. Three-dimensional geometric computations,[2] finite element analyses,[3,4] photoelastic studies,[5] and strain gauge measurements[6] were considered the standard for biomechanical evaluations. The consensus from these bench investigations was that implant fixed partial prostheses, especially cantilevered designs and permutations with high crown-to-implant ratios, generated excessive stress deformation to the peri-implant bone. However, the actual fatigue failure of the bone surrounding implants was never considered, and the relatively high stress levels were not clinically significant. These data led to overengineering and overtreatment. Ironically, Guyatt et al[7] published their work on the Hierarchy of Evidence in the 1990s, but their assessment of the high risk of bias in the external validity of in vitro studies was not acknowledged. What is noteworthy is that the same myopia in the algorithms building large language models to develop artificial intelligence (AI) platforms is spawning clinically irrelevant answers to questions regarding optimal dental treatment. For example, unfiltered published articles are generating consensus statements for ChatGPT.[8] This flaw in the platform has been addressed in OpenEvidence, which is designed to stratify and prioritize the strength of studies based on their methodological rigor, preferentially drawing on systematic reviews and meta-analyses.[9]

A significant application for AI has been in oral implantology, and the keen interest in enhanced data collection has spurred the use of highly accurate calibration systems such as millimeter-scale alveolar bone guides, classification of bone density, and mapping anatomic structures.[10] Once again, whether such diagnostic software datasets would eliminate critical errors in treatment outcomes needs to be considered. These AI metrics can be seductive, confusing extreme precision with the highest quality of care. However, there are appropriate targets for AI's image analysis capability, such as classifying implant systems, identifying pathologies, and reducing intra-operator and inter-operator error in assessing radiographic implant bone levels.[11] The focus on AI should be to amplify clinicians' skills by increasing diagnostic acumen and reducing workload while using the litmus of clinical significance. This lesson has been decades in the making.

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