

## Practical Solutions for Working with Electronic Health Records Data – References

### ***EHR Data Structure and Quality***

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