MY NDSU THESIS — SANDBOX

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MY NDSU THESIS — SANDBOX

By

The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

DOCTOR OF PHILOSOPHY

SUPERVISORY COMMITTEE:

Approved:

Date Chair

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1. TEST CHAPTER FOR NDSU THESIS CLASS SANDBOX

This "`ndsu-sandbox.tex`" file can be used as a sandbox to try out things in the actual NDSU thesis environment. Things tested here (including the bibliography) can be readily inserted into the original thesis/dissertation document. Therefore, this lightweight source will be convenient to test things out. So, go for it — and remember anything is possible by LaTeX (almost!?).

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