Big Data is Not About the Data!

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(Talk at *SearchCIO360*, *TechTarget* 11/19/2013)

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- In each: without new analytics, the data are useless

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  2. Worldwide cause-of-death estimates for

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  - Other applications to insurance industry, public health, etc.

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For more information

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