"I'm interested because....": What motivates women to take data science courses.

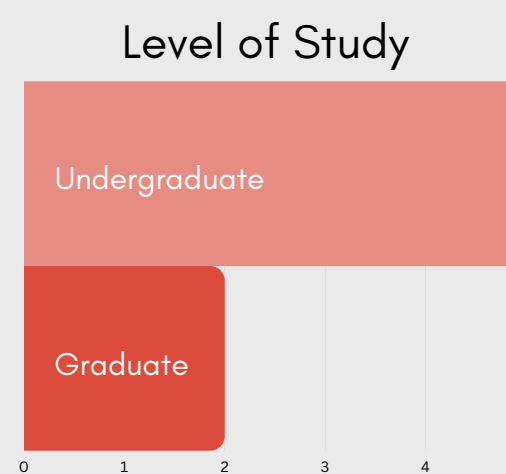**JEANNE MCCLURE**
HAMID SANEI
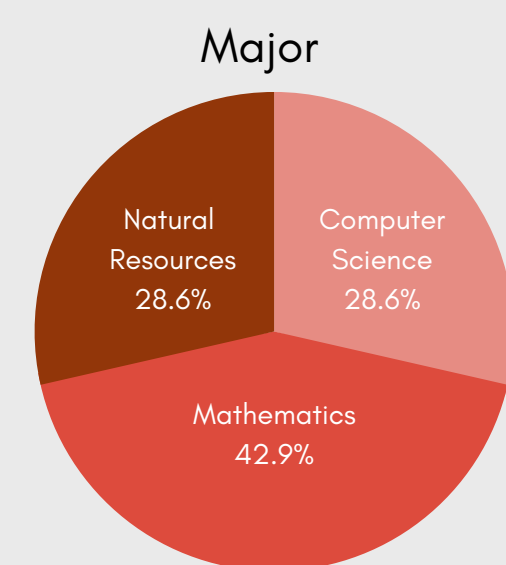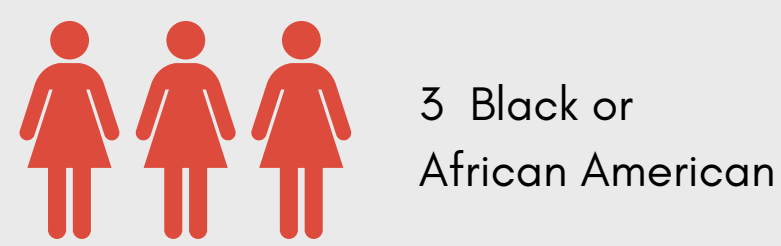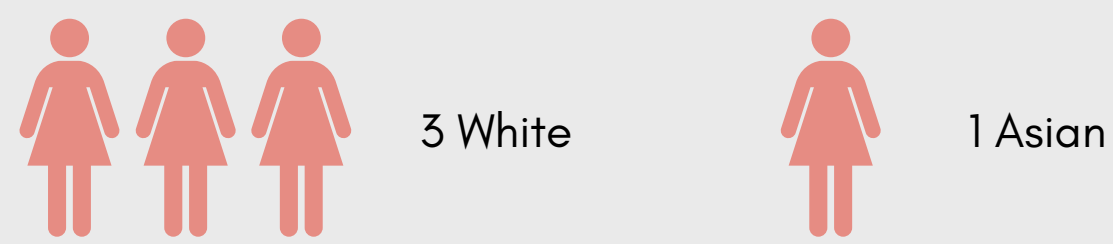**SUNGHWAN BYUN**

RATIONALE:

Most of the world's data scientist teams that make decisions on data collection, organization, analysis, and communication **are men**. **Less than 24%** of all Data Scientists **are female** (Young et al., 2021). The gender imbalance leads to a source of bias in many datasets, consciously or not.

To address this issue, it is crucial to **increase diversity and representation in the data science community** (Kuhlman et al., 2020). One initiative would be to encourage more women to pursue careers in data science. An **expectancy-value theory (EVT)** lens may explain how individuals make decisions and choices based on their **beliefs about their ability** to perform a task and their **perceptions of the task's value or importance of learning data science** (Wigfield & Eccles, 2000).

RESEARCH QUESTIONS:

What motivates women in project based data science courses?

PARTICIPANTS:

3 White   1 Asian

3 Black or African American

Major

Natural Resources 28.6% | Computer Science 28.6%
Mathematics 42.9%

Level of Study

Undergraduate
Graduate

0 1 2 3 4 5

QUALITATIVE METHODOLOGY:

Data Collection
7 semi structured Interviews

Deductive Theory-based Coding

5 a priori codes
62 codes

17 Ability Expectancy codes

4 Attainment codes
12 Interest codes
22 Utility codes
7 Cost codes

Inductive Thematic Coding

12 Emerging Themes

PRELIMINARY INDUCTIVE RESULTS:

Expectancy ABILITY

What are the perceived ability in DS?
- Enhanced perceived ability due to relevance of dataset.
- Enhanced perceived ability due to opportunities to collaborate
- Enhanced perceived ability due to DS resources and support.

COST

What are the costs of learning DS?
- The effort it takes for debugging is more than they want to do.
- Using one IDE over another requires giving up the preferred IDE.

INTEREST

How is DS valued as inherently interesting?
- Joyful experience of doing DS (in context & autonomy).
- General interest in data science and working with data.

ATTAINMENT

How is DS important for the sense of self?
- Learning data sscience due to a marginalized identity.
- Learning data science based on disciplinary identity.

UTILITY

What goals are valuable to stay motivated in DS?
- Utility to carry out research with DS tools.
- Utility to prepare for DS careers.
- Utility to advance in DS learning progression (1-credit hr Course).

THEORETICAL FRAMEWORK:

Expectancy Value Theory
(ECCLES ET AL., 1983, WIGFIELD & ECCLES, 2000)

EXPECTANCY
The usefulness or importance of a particular task to an individual's current or future goals.

TASK VALUES

Utility
The usefulness or importance of a particular task to an individual's current or future goals.

Interest
The inherent enjoyment or satisfaction an individual perceives that he or she will obtain from engaging in a task.

Cost
The amount of effort required by a task, and emotional cost.

Attainment
The importance of a task to an individual's self-concept or identity.

DISCUSSIONS

- **Using relevant data** could lead to **enhancing multiple elements of motivation** such as **perceived ability and interests**.
- **Woman value low stake easy access one-credit DS course** to experience DS as a future career and learning progression.
- The motivational drive behind enrolling in an introductory 1-credit hour course is two fold:
  - workload and time commitment are relatively low compared to courses with higher credit values.
  - acts as a stepping stone towards undertaking more advanced data science courses.
- **Woman are motivated in data science tasks** that they perceive will be **valuable for their research**.

FUTURE DIRECTION

There's some evidence that **social identities can be motivating factors** for women **to take DS courses and pursue DS careers** however a more in depth study is needed to analyze those findings

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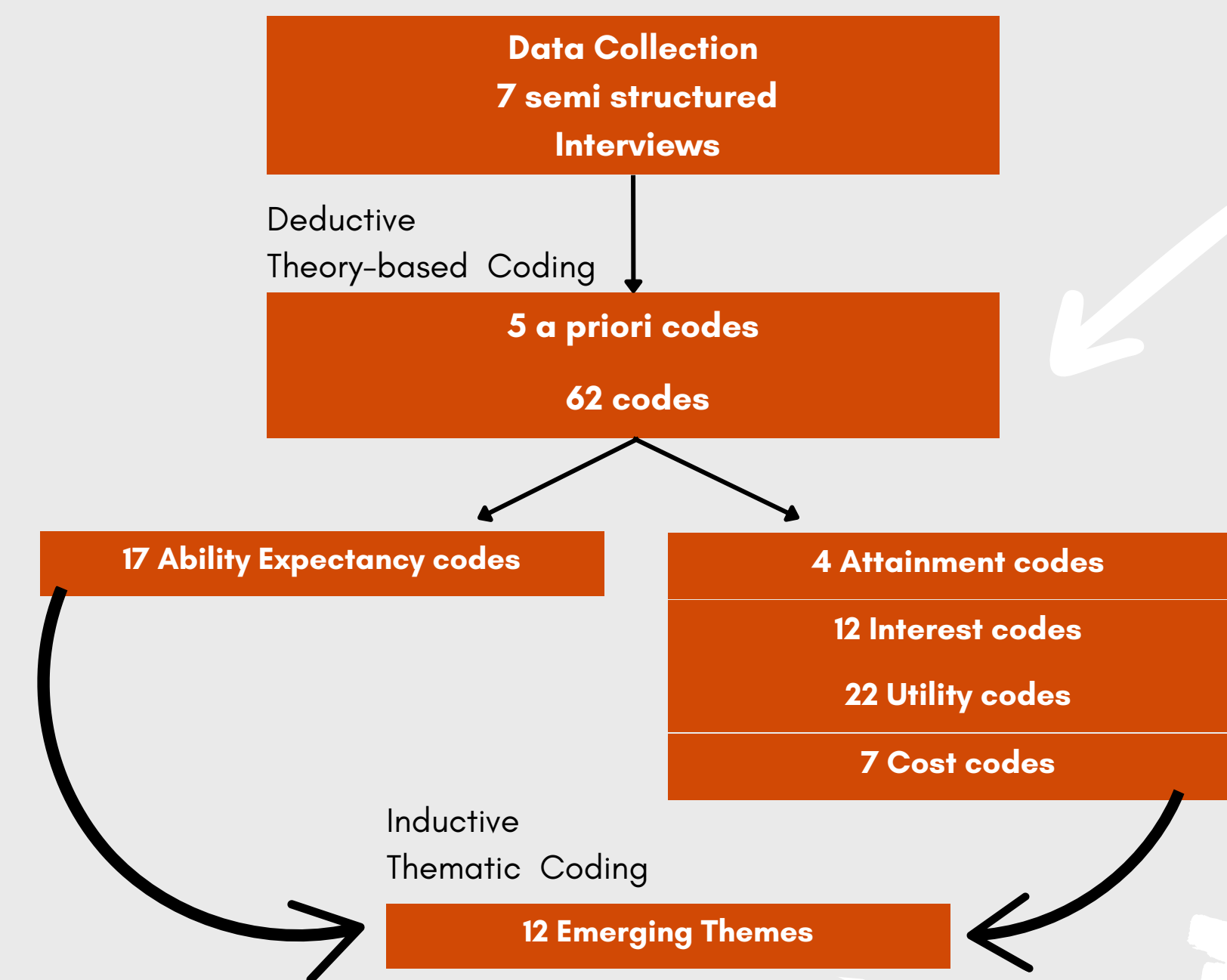Wigfield, A. (1994). Expectancy-value theory of achievement motivation: A development perspective. Educational Psychologist, 6(1), 49-78.
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