

USING DATA-DRIVEN APPROACHES TO ADDRESS PSYCHOLOGICAL BARRIERS IN INTERDISCIPLINARY EDUCATION: BRIDGING SOCIAL SCIENCES AND TECHNOLOGY FOR EQUITABLE LEARNING

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Abstract

The rapid evolution of job markets needs continuous skill development to ensure that individuals stay relevant and adaptable in the competitive dynamic market. In the era of Artificial Intelligence, transformative fields have significant opportunities for learners from different academic backgrounds. However, non-technical students face psychological barriers which hinders their ability to learn these high demand skills. This study explores these barriers qualitatively, and identifies challenges faced by non-technical learners and the strategies to overcome them. The study conducted through a questionnaire filled out by 58 respondents finds that many students successfully overcome these obstacles by leveraging AI tools and seeking mentorship that simplified complex concepts and boosted their confidence. Upon these insights, this research paper proposes the use of data driven approaches to address psychological barriers in interdisciplinary education. The creation of customized learning programs, and tools designed to help students evaluate potential outcomes and benefits if they transit in this with their current educational background could play a major role in motivating continuous skill development and make the technical field more accessible. By addressing these psychological and practical challenges faced by non-technical learners. This innovative approach will help break the hurdle and will make people work confidently in any dynamic landscape of working professionals.

Keywords: *Career Adaptability, Data Driven Education, Psychological Barriers, Skill Development, AI Mentorship Impact*

Introduction

The development of interdisciplinary education is essential to ensure equity and inclusion in the global job market. Non-technical students have tremendous psychological barriers that include imposter syndrome, math anxiety, and fear of programming, which act as a deterrent to learning data science and machine learning (DSML). Through a data-driven approach rooted in social sciences, this research delves into the barriers and outlines actionable interventions to improve decision-making and social impact. An AI tool, mentoring, and student-specific learning path have been seen as effective remedies in the identified challenges through the survey of 58 respondents, thus showing a great potential from data-driven framework-based learning for an inclusive systems approach, and interdisciplinary collaboration, allowing students to build adaptive professional selves.

Review of Literature

Kinnunen, P., & Malmi, L. (2006).

This research looks at how feelings, social connections, and study habits affect why students leave introductory programming courses. It points out major challenges, like getting frustrated with fixing code and not having enough help, which are similar to the issues that students without a technical background encounter in data science.

Collister, L., & Mateas, M. (2018).

This study highlights how important it is to have easy-to-use tools and clear teaching methods for people who are not experts in machine learning. It points out that feelings like self-doubt and fear of failing can make it hard for these learners to get involved and do well.

Holmlund, T., Leskinen, P., & Peltonen, J. (2020).

This study looks at how feelings affect learning data science, especially for those without a technical background. It points out that getting frustrated and being afraid to fail can hurt how well someone learns. The study also recommends creating friendly learning spaces to help with these issues.

Bandura, A. (1997).

Bandura's idea about self-efficacy highlights how important it is to believe in ourselves when trying to do things. The study helps us see how this belief affects students who are not studying tech subjects,

especially in terms of their motivation and their ability to keep going while learning about data science.

Tan, P. N., & Steinbach, M. (2018).

This study looks at the difficulties non-STEM students have when learning data science. It points out problems like feeling overwhelmed and not having enough basic knowledge. The study suggests using teaching methods that combine different subjects to help solve these problems better.

Zhang, D., & Wang, T. (2017).

The study looks at how to teach data visualization to students who do not study science, technology, engineering, or math. It highlights how helpful interactive tools and practical activities can be. These methods help make complicated ideas clearer for learners who may not know much about programming.

Research Objectives

1. To investigate the psychological barriers that deter non-technical students from engaging with DSML.
2. To explore the role of data-driven interventions like AI tools and mentorship in overcoming these challenges.
3. To evaluate the impact of targeted interventions on learners' confidence and motivation.
4. To propose frameworks for educators, policymakers, and learning platforms to implement scalable solutions for interdisciplinary education.

Research Methodology

1. Research Design

This study uses a descriptive research plan to look at the mental blocks that non-technical learners aged 18 to over 45, face when trying to learn data science and machine learning. This plan is fitting because it aims to gather detailed information about what participants think and experience without changing any factors.

2. Data Collection

- Method: Online questionnaire via Google Forms targeting Non-technical students.
- Sample Size: 58 respondents.
- Sampling Technique: Snowball sampling to ensure accessibility and relevance. •
- Questionnaire Distribution: Shared through social media, email, and non-technical student groups interested in data sciences and machine learning.

3. Data Analysis

Techniques: Descriptive statistics (frequency, percentages) to summarize responses.

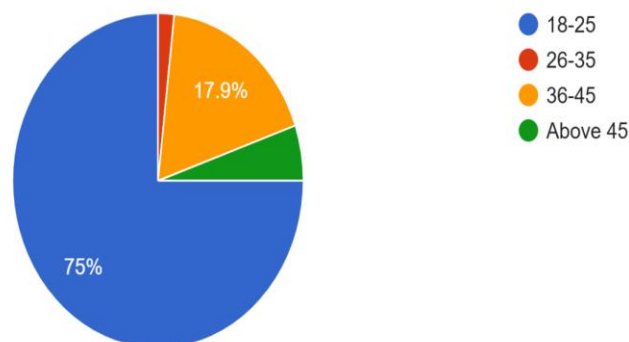
4. Ethical Considerations

- Informed Consent: Participants will be briefed on the research purpose and their right to withdraw.
- Confidentiality: Responses will remain anonymous and data will be used solely for research purposes.
- Transparency: Clear communication about data usage and findings will be shared upon request.
- Neutrality: The questionnaire will avoid biased or leading questions to ensure authentic responses.

Data Analysis and Interpretation

Q1>What is your Age Group ?

What is your Age Group
56 responses



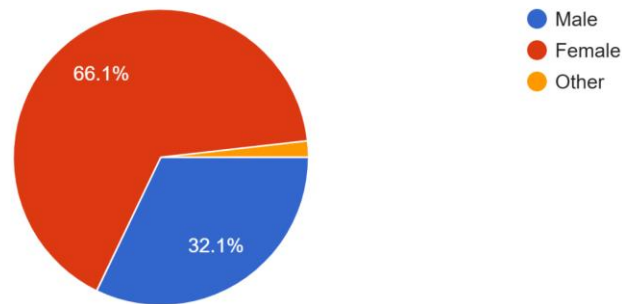
Interpretation:

- Majority (75%) of respondents are aged 18-25.
- Respondents aged 36-45 are 17.9 % .
- A small percentage of respondents are aged 26-35.
- Few respondents are above 45.

Q2>What is your Gender?

What is your Gender ?

56 responses



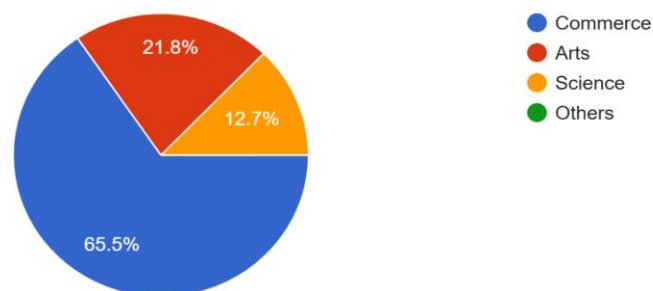
Interpretation:

- Majority of respondents are male (66.1%)
- Female respondents are (32.1%)
- Small percentage identifying as other (1.8%)

Q3>What is your current educational background?

What is your current educational background?

55 responses



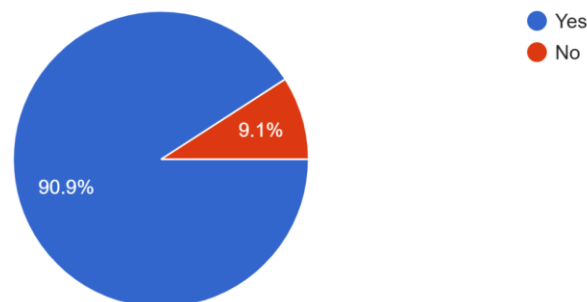
Interpretation:

- Commerce background respondents are 65.5%
- Arts background respondents are 21.8%
- Science background respondents are 12.7%

Q4>Have you attempted to transition into the field of data science and machine learning(DSML)?

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55 responses



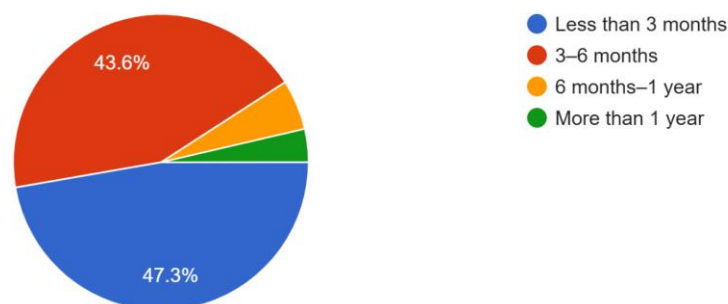
Interpretation:

- Response shows that 90.9% respondents attempted to transition
- And 9.1% did not attempted to transition

Q5>If yes, how long have you been learning or working in Data Science and Machine Learning?

If yes, how long have you been learning or working in Data Science and Machine Learning?

55 responses



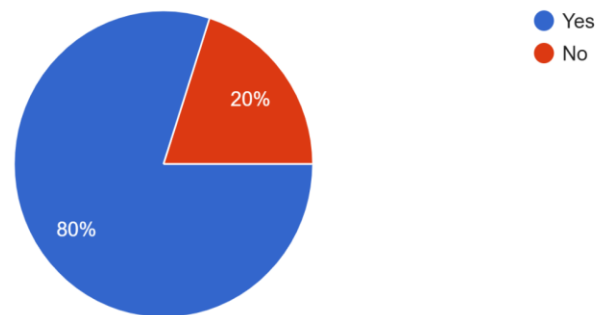
Interpretation:

- 47.3% respondents have been working in this field for less than 3 months
- 43.6% respondents have worked between 3 to 6 months
- few have worked between 6 months to 1 year
- few already have an experience of more than 1 year

Q6>Did you initially feel hesitant to enter Data Science and Machine Learning due to your non-technical background?

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55 responses



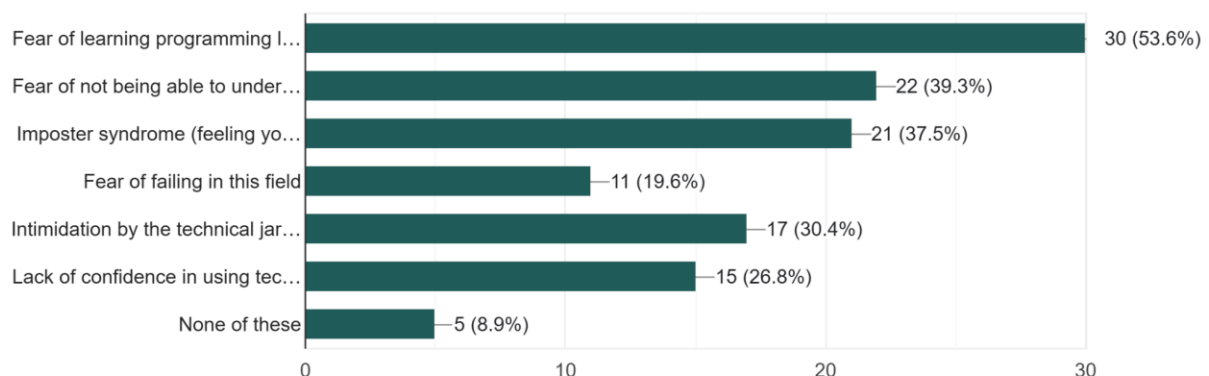
Interpretation:

- 80% participants did not feel hesitant to enter DSML
- 20% did feel hesitant to enter DSML

Q7>Which of the following psychological barriers did you experience before or during your transition into Data Science and Machine Learning? (Select all that apply)

Which of the following psychological barriers did you experience before or during your transition into Data Science and Machine Learning ? (Select all that apply)

56 responses



Interpretation:

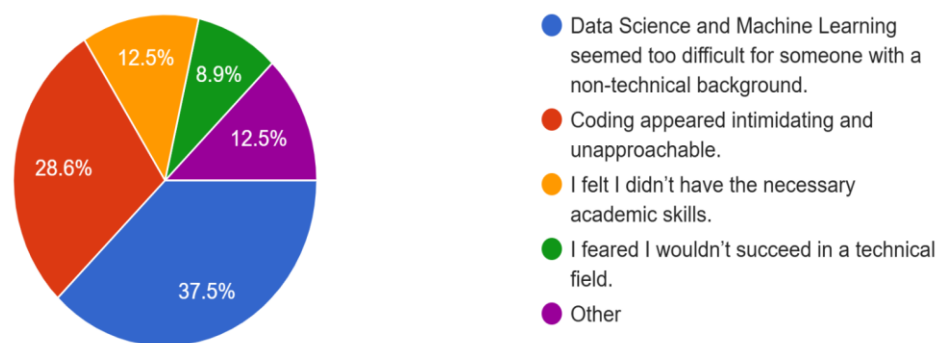
- Fear of learning being the most common at 53.6%
- Fear of not being good enough at 39.3%

- Imposter syndrome at 37.5%
- Fear of failing in this field at 19.6%
- Intimidation by the technical jargon at 30.4%
- Lack of confidence in using technology 30.4%

Q8>What was the main reason for your hesitation or fear of entering Data Science and Machine Learning?

What was the main reason for your hesitation or fear of entering Data Science and Machine Learning ?

56 responses



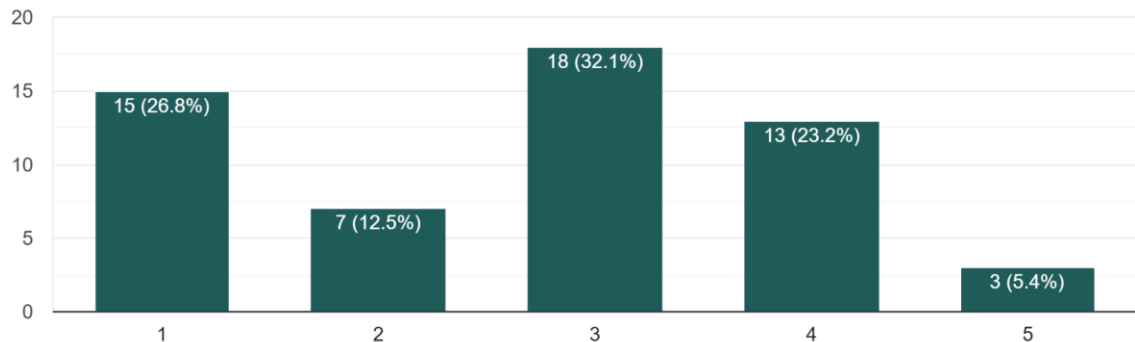
Interpretation:

- Data Science and Machine Learning being the most intimidating at 37%
- Coding concerns at 29.6%
- Academic skill concerns represent 13%
- 9.3% feared lack of success in technical fields
- 11.1% cited other reasons
- Together, technical skill intimidation (data science and coding) accounts for about two-thirds of all concerns at 66.6%.

Q9>If yes, how strongly did you experience imposter syndrome? (1 = Not at all, 5 = Very strongly)

If yes, how strongly did you experience imposter syndrome? (1 = Not at all, 5 = Very strongly)

56 responses



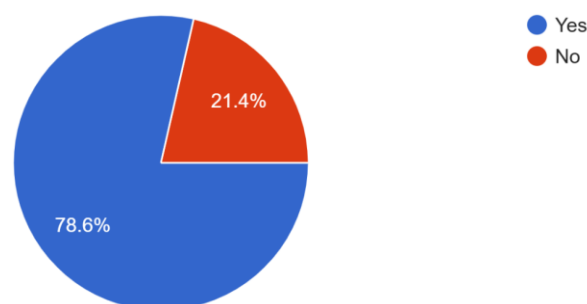
Interpretation:

- Category 3 having the highest frequency at 32.1% (18 responses)
- Category 1 at 26.8% (15 responses)
- Category 4 at 23.2% (13 responses)
- Categories 2 show lower frequencies at 12.5% (7 responses)
- Category 5 shows 5.4% (3 responses)

Q10>Did you feel that being from a non-technical field would make it harder to succeed in Data Science and Machine Learning?

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56 responses



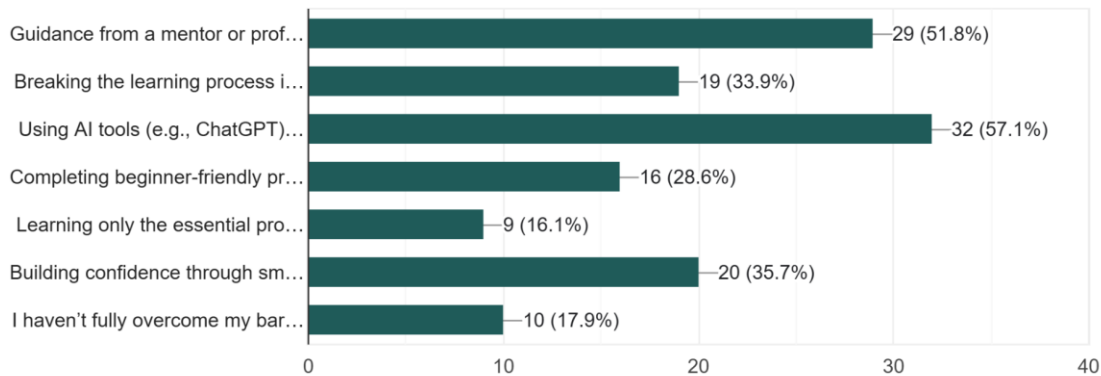
Interpretation:

- A strong majority (78.6%) answered "Yes" being it harder to succeed
- (21.4%) answers "No"

Q11>What helped you overcome your psychological barriers to entering Data Science and Machine Learning? (Select all that apply)

What helped you overcome your psychological barriers to entering Data Science and Machine Learning ? (Select all that apply)

56 responses



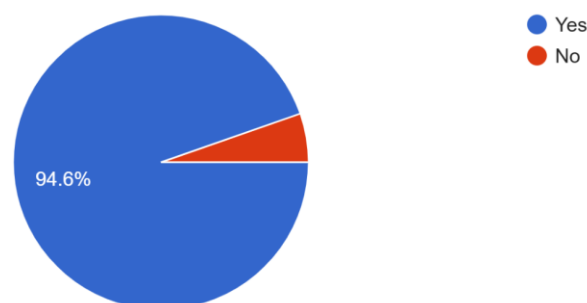
Interpretation:

- The methods for overcoming psychological barriers in DSML were:
- AI tools like ChatGPT (57.1%)
- mentor guidance (51.8%)
- Still 17.9% haven't fully overcome their barriers

Q12>Did achieving smaller milestones (e.g., learning basic python) help you feel more confident in your journey?

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56 responses



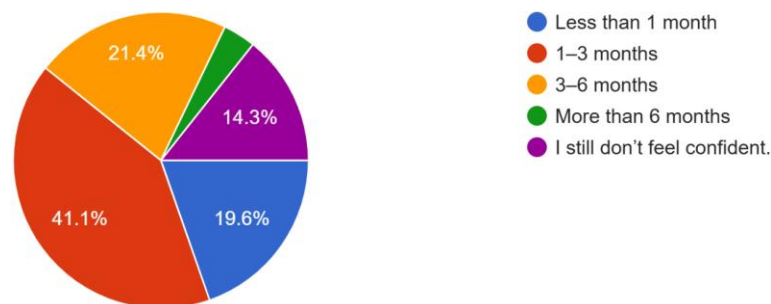
Interpretation:

- 84% of respondents felt more confident in their journey
- Only 16% did not feel more confident

Q13>How long did it take for you to feel confident after starting your learning process?

How long did it take for you to feel confident after starting your learning process?

56 responses



Interpretation:

The chart shows how long it took people to feel confident after starting their learning process:

- Most (41.1%) felt confident within a month
- 21.4% felt confident in 3-6 months
- 19.6% felt in less than 1 month
- 14.3% still don't feel confident
- Few respondents took more than 6 months

Analysis and Discussion

Analysis

1> **Barriers Identified:** The most common barriers included fear of programming at 53.6%, imposter syndrome at 37.5%, and intimidation by technical jargon at 30.4%.

These barriers are deeply located in systemic inequities, such as unequal access to science , technology ,engineering and mathematics education and limited exposure to technical skills.

2> **AI Tools as Enablers:** AI tools like ChatGPT led 57.1% of the participants to simplify technical concepts and reduce intimidation. These tools offer real-time support, allowing learners to move forward independently while removing psychological concerns.

3> **Mentorship Role**

51.8% of respondents felt that mentorship was necessary in dealing with psychological barriers since mentors provided personal guidance and emotional support.

Mentorship creates a feeling of belonging that is necessary for non-technical students entering the technical domain.

4> **Self-Efficacy by Means of Milestones:**

84% of respondents showed increased confidence from the attainment of smaller milestones: learning the basics of Python, completing beginner projects, and others.

Incremental achievements act as psychological reinforcements that build motivation and promote resilience in the learner.

Discussion

The findings of this study focuses on the psychological barriers and motivational factor faced by non technical students adopting data sciences and machine learning. Several critical insights come out after interpreting the data-

1> **Psychological Barriers as Social Constructs:** Psychological barriers, like fear of failure and math anxiety, show deeper system failures, including the underrepresentation of non-technical students in science , technology ,engineering and mathematics related fields. Proper reforms that address these barriers must also integrate principles of behavioral psychology with technical education.

2> **Data-Driven Interventions for Inclusive Education:** AI-based tools and mentorship programs are important data-driven solutions enhancing educational accessibility among non-technical students. These programs analyze learner behaviors and needs, thus creating personalized solutions that reduce psychological barriers and strengthen engagement.

3> Linking Technical Education and Social Sciences: Integrating the social science inputs, including confidence building and emotional resilience, in technical education for overall learning. The interdisciplinary approach not only benefits individuals but also encourages collaboration and societal impact by diversifying technical workforces which can be ensured through engagement.

4> Empowering Learners for the Future: By addressing psychological barriers with incremental learning, mentorship, and decision analytics, learners will be more confident to take up technical fields. This empowers them to adapt to a profession which is future-ready.

Implication

1. For Instructors:

- a. Create learning paths that incorporate psychological barriers, like the fear of failure, using small achievable steps on complicated subjects.
- b. Using real-time data to analyze who is struggling and help the student.

2. For Policy Makers

- a. Implement interdisciplinary study through scholarships and marketing campaigns to bring more students into the trending job market.
- b. Enhance initiatives which are aligned to inclusiveness and build interdisciplinary skills through multidisciplinary programs.

3. For Learning Platforms

- a. Create adaptive learning to adapt content to the learner's profile.
- b. Integrate mentorship and community support system to have collaboration and reduce isolation.

Conclusion

This research highlights the psychological barriers that a non-technical student encounters in dealing with data science and machine learning. It's clear that fear of programming, math anxiety, and imposter syndrome are massive deterrents. But such detriments can be eliminated with targeted strategies like personalized mentorship, AI-driven learning tools, and flexible, customized educational pathways.

The study reminds us to have significant boosts for self-confidence and motivation, as well as infusing a growth mindset in non-technical learners. This lays the groundwork to have this positive and healthy

attitudes that help individuals work over their fears with technical domains in order to succeed. However, the current study also represents a shared role of educators, policymakers, and learning platforms within it to design a powerful, inclusive learning ecosystem.

It may even include participation by hands-on industry mentoring to give a practical form of interventions that bridges the gap between a non-technical learner and the acquisition of technical skills. Such research works well in-line with the New Education Policy vision of 2020 that demands for interdisciplinary learning and giving of digital competencies to the learners.

Future studies might focus on developing programs like customised learning pathways and tools that will aid in the evaluation of the long-term effects of such interventions and tell success stories of non-technical learners transitioning into data sciences and machine learning, which would make technical education more relevant and accessible for a broader set of learners.

Future Work

Building on the insights obtained from this study , several opportunities exist to further advance this study to bridge the gap between non-technical learners and technical skills by leveraging innovative approaches:

1>Develop adaptive learning systems that use behavioral data to predict and address learner challenges - Offering personalized interventions like feedback and simplified resources. By integrating social science principles, they promote inclusivity and equitable interdisciplinary education.

2> Development of a customised learning pathway program - A program will be developed to offer a personalized learning pathway to non-technical learners which will guide them to do the essentials in a given time frame to excel in the field. It will be a step by step schedule.

By breaking down the learning process into manageable and measurable tasks this will help them to reduce psychological barriers while enhancing their confidence and self-belief.

3> Designing a return-on-investment (ROI) assessment tool - Another initiative involves developing a program which will tell non technical learners the potential return on investment if they transit their career in technical fields like salary increases , career opportunities, etc .

This program will show the learners a tangible value offering clarity and eventually increasing their motivation and confidence.

4> Conducting in-depth interviews for broader insights - Beyond quantitative surveys , future research will incorporate in-depth interviews with non-technical learners who are transiting their career in the technical field. These interviews will let us know their personal experiences , emotional challenges and their coping strategies to barriers. It will offer new perspectives that cannot be collected through questionnaires alone.

This will bring a human element to this research which will make it more relatable and efficient.

5>Career Transition Tales for inspiration -The future research work would have individual stories who have transitioned into technical fields.By showcasing relatable examples, study will inspire readers and demonstrate that barriers can be overcome with the appropriate support and mindset.

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