Using Large Language Models to Increase Accessibility in Physics Education

THE PHYSUALISER

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ABSTRACT

Artificial Intelligence is set to transform how we approach education. Much previous research has been related to AI's performance in exams [1]. However, in this paper, I will investigate how AI can affect day-to-day learning, especially among those with accessibility accommodations or special educational needs. I found that the default ChatGPT provided somewhat reasonable support although this could be substantially enhanced through the use of custom instructions, to create the Physualiser. The Physualiser was tested by comparing its performance to default ChatGPT, using information related to but outside its knowledge base, and using more complex physics concepts. Throughout these tests, it had a strong performance although there are recommendations for improvements and further research applications.

Keywords: Large Language Model, Artificial Intelligence, Universal Design for Learning

1. Neurodivergence in Physics Education and Learning

Neurodiversity is defined as the naturally occurring variation in the ways that humans perceive, experience and interact with the world, encompassing neurodevelopmental differences such as autism, attention deficit hyperactivity disorder (ADHD), dyslexia, developmental language disorder (DLD), dyscalculia and dyspraxia [2]. Given the importance of cognitive diversity in finding solutions to the world's complex problems, it is essential that neurodivergent students are encouraged and supported in the ways they require.

There is a plethora of special educational needs (SEN) learning methods that are applicable across a variety of specific disorders. For example, digitisation of content, text-to-speech software/Dictaphones and synchronous/asynchronous interactions [2][3]. The main aim of these accommodations is to make students feel as comfortable as possible by reducing anxiety and ambiguity. Generally, it is important to have diverse modes of interaction and cognition as well as repeated, spaced interactions with content.

The Universal Design for Learning provides a framework of three principles to support and encourage students, reflecting the basic neurology of the learning brain [4][5]:

1. **Engagement** – no one way to extrinsically engage students by the same rewards, nor develop intrinsic motivation in the same way

   This empowers learners so they are motivated and sustain interest. This can involve creating games around skillbuilding, giving opportunities for movement to help those who may be dynamic learners and ensuring the relevance of assignments is clear.

2. **Representation** – no one way of representing information/teaching that is best for all students

   This involves giving instructions in more than one way. For example, reading instructions aloud, using diagrams, or demonstrating in person or with a video.

3. **Action & Expression** – no one way of expression that is best for students, nor one kind of scaffolding/support to help them

   This means that students can demonstrate their learning through whatever medium is most comfortable for them. For example, an oral presentation, group project, creative endeavour (video, comic strip etc.), rather than a pen on paper test.

Crucially, these accommodations are provided to all students, not just those with special needs. This means that those with disability accommodations are not singled out, helping to reduce stigma, and acknowledges the fact that many learning conditions go undiagnosed and unnoticed, especially in large classroom environments.

2. Background on Large Language Models

Large Language Models (LLMs), such as ChatGPT, are sophisticated text generation programs which can create compelling and detailed text on a variety of topics. GPT stands for Generative Pre-trained Transformer. ‘Pre-trained’ means it is a model that has learned from a massive amount of data. In other words, it can be further trained and finetuned. A ‘Transformer’ is a specific type of neural network that is underlying the current boom in AI. It can do voice-to-text, text-to-voice, text-to-image and even language translation. The aim of a GPT is to set up a flexible model with tunable parameters, rather than just code, and this is the simplest form of machine learning [6].

I had already started to develop ideas based on my experiences solving physics questions. As a physics student, the first piece of advice given by a tutor is often to ‘draw a picture’. Therefore, it would be beneficial if this step could be automated through a few keystrokes. My concept involves utilising a GPT model to generate a diagram or illustration for the problem, thereby visualising the physics. Additionally, could a GPT model perform the inverse task, such as providing a descriptive caption for a diagram from a textbook? Other ideas I considered included a ‘reverse Dictaphone’ which would narrate the instructions of a question aloud, and a feature that creates a video representation of the question in action.

3. Initial tests: Experimenting with GPTs in ChatGPTPlus

I began to try out existing GPTs available on the ChatGPT4o marketplace. I used two questions taken from weekly problems I had studied as part of the *Foundations of Physics 1* first year undergraduate course at Durham University. The first question was a kinematics problem (Figure 1a, henceforth referred to as question 1) and the second was a quantum mechanics problem (Figure 1b, henceforth referred to as question 2). These represented opposite ends of the conceptual abstractness/complexity spectrum covered in first year physics. I used five GPTs: Audio Generator, Diagrams <Show Me>, Physics Oracle, Math Solver and Mermaid Charts. In each case the GPT was given the prompt: *draw a diagram of this problem [problem pasted]*.

a) A bead with a small mass m sits on top of a ball-bearing with a large mass M. The ball-bearing is a height 2.0 m above a steel table. The balls are dropped, and the ball-bearing hits the bead as it bounces upwards. Neglecting air resistance, to what height does the bead bounce? (You can assume here that all collisions are elastic, and the masses are point masses.)

b) A particle is described by a wavefunction whose spatial part is

$$\psi(x) = \begin{cases} Ae^{bx} & x < 0 \\ Ae^{-bx} & x > 0 \end{cases}$$

where A and b are real constants.

Figure 1: Sample questions, taken from Foundations of Physics 1 weekly problems, used to experiment with GPTs. (a) is taken from the Mechanics 1 part of the course, (b) is taken from the Quantum Mechanics part of the course

a) Audio Generator

I used this GPT to read out question 1. However, words often overlapped and dialogue was not at all fluent [7]. I also tried other audio GPTs that claimed to be able to narrate text but they could not do it 'within the time constraints'. Instead, text was given back slightly reconfigured, for example as a podcast script, or I was directed to other websites that could do this for me. Therefore, I decided that audio was not a useful avenue to pursue and would unlikely be helpful to most students in classrooms anyway. Thus I turned my attentions to text-to-image GPTs that would allow students to draw diagrams of the physical setups of their problems.

b) Diagrams <Show Me> [8]

The next GPT I used was Diagrams <Show Me>. The outputs are shown in Figures 2-7. The flowchart in Figure 2 was produced following a suggestion from the GPT to improve the diagram by adding additional details concerning velocities and energies into each step, which I implemented. Figure 3 shows a variety of ball bearings, presumably to demonstrate its trajectory. The table has an unexplained hole, the scale on the right-hand side is not accurate and labels are incomplete. Consequently I decided to refine my prompt, see Figure 4. Further refinement was undertaken (see Figure 5) as the first adjustment produced a highly inaccurate diagram; arrows show the ball to move in two directions. Unfortunately Figure 5 proved to be the most complex and challenging to interpret. This highlights the need for highly specific prompts and indicates that some topics may not be compatible with certain models.

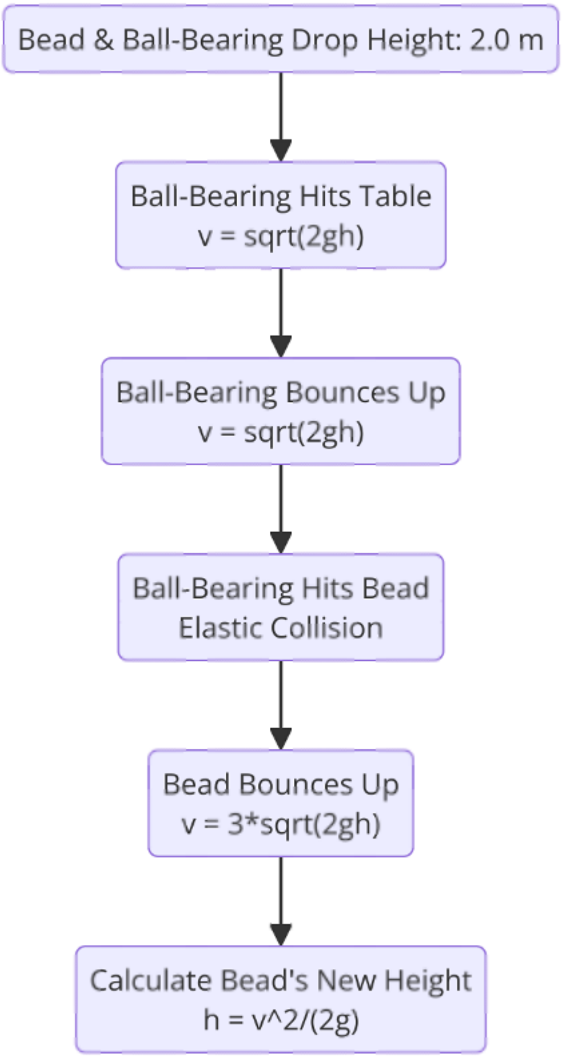

Figure 2: Flowchart produced by Diagrams <Show Me> GPT when asked question 1

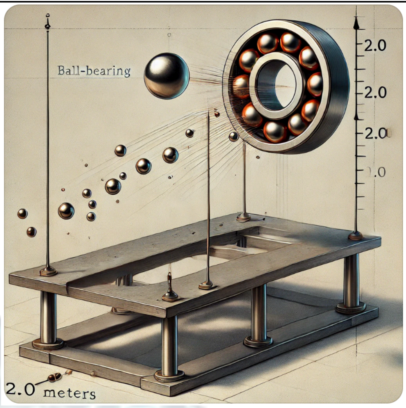

Figure 3: Picture produced by Diagrams <Solve Me> GPT when given the prompt "draw a picture of the experiment"

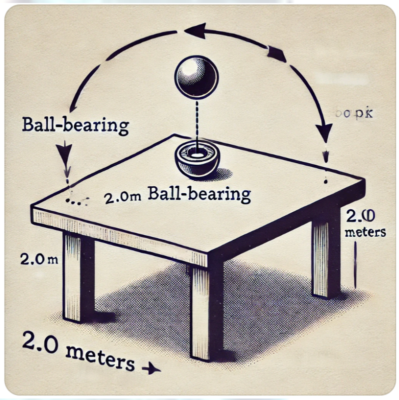

Figure 4: Picture produced by Diagrams <Solve Me> GPT when Figure 3 refined by the prompt "make the picture more simple"

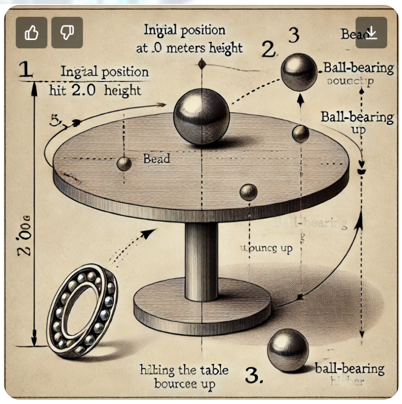

Figure 5: Picture produced by Diagrams <Solve Me> GPT when given the prompt "draw a picture of the experiment, like you would to solve the question"

Figures 6 and 7 show the results from question 2 [9]. The GPT's first response (Figure 6) clearly outlines the key components of the problem but provides no visualisation of the physics. The refined prompt (Figure 7) is merely a sketch of the mathematical equation. While this is clear, it contributes little to the conceptual understanding of the problem.

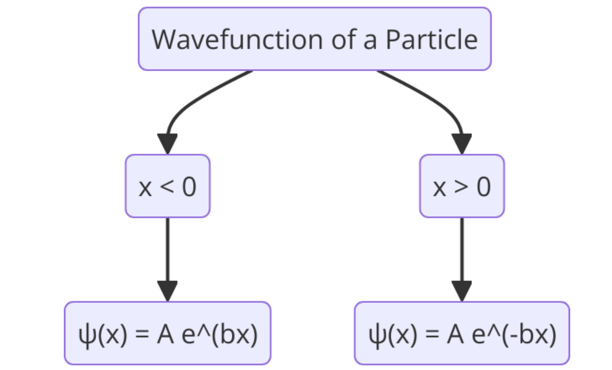

Figure 6: Chart produced by Diagrams <Show Me> GPT when asked question 2

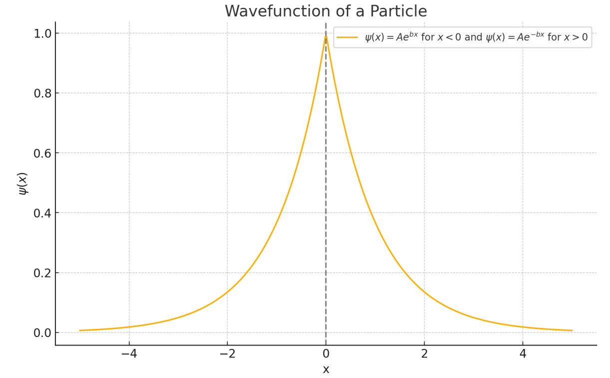

Figure 7: Graph produced by Diagrams <Show Me> GPT when questions 2 prompt refined to "draw a graph"

c) <u>Physics Oracle</u>

Figure 8-11 show the results from the Physics Oracle GPT. This GPT correctly solves the question but does not create a picture like those above. Instead, it 'draws diagrams' in text. Although these diagrams are two-dimensional and very simple, they do clearly re-represent the problems and do not overcomplicate the scenarios.

```yaml
Initial Drop:
Bead + Ball-Bearing:       |
                           |
                          (o)   -->  2.0 m above table

Impact with Table:
Ball-Bearing rebounds:     (↑)
Bead descends:            (↓)

Elastic Collision:
Ball-Bearing (Up):          |
Bead (Up at 12.52 m/s):    (↑)

Final Height of Bead:
Reached Height:           8.0 m
```

Figure 8: ASCII Art diagram produced by Physics Oracle GPT when asked question 1 [10]

```
Initial Drop:
------------------------------
|                 |
|   o (Bead)          |
|   O (Ball-Bearing)      |
|                 |
|                 |
|                 |
|      2.0 m           |
|                 |
------------------------------
|    Steel Table         |
------------------------------
Impact with Table:
------------------------------
|                 |
|                 |
|   O (Ball-Bearing) ↑      |
|                 |
|                 |
|                 |
|      2.0 m           |
|                 |
------------------------------
|    Steel Table         |
------------------------------
Collision in Air:
------------------------------
|                 |
|   o (Bead) ↓          |
|                 |
|   O (Ball-Bearing) ↑      |
|                 |
|                 |
|      2.0 m           |
|                 |
------------------------------
|    Steel Table         |
------------------------------
After Collision:
------------------------------
|                 |
|   o (Bead) ↑ 12.52 m/s    |
|                 |
|   O (Ball-Bearing) ↓      |
|                 |
|                 |
|                 |
|                 |
------------------------------
|    Steel Table         |
------------------------------
```

Figure 9: ASCII Art diagram produced by Physics Oracle GPT when given the prompt "draw a picture of the scenario" [10]

Although question 2 was solved correctly, the GPT also produced an error message (Figure 10). Furthermore, the graph produced (Figure 11) is near identical to that produced by Diagrams <Show Me> (Figure 7). The only difference is that the coefficients of the wavefunction are defined in terms of b rather than an unknown, A.

```
\sqrt{b} e^{bx} & \text{for } x < 0 \\
\sqrt{b} e^{-bx} & \text{for } x > 0
\end{cases} \]
The wavefunction exponentially grows for \(x < 0\) and decays for \(x > 0\), with
a normalization constant ensuring the total probability is 1.
Is there anything else you would like to learn or explore?
&#8203;:citation[oaicite:0]{index=0}&#8203;
```

Figure 10: Error message given by Physics Oracle GPT in response to question 2 [11]

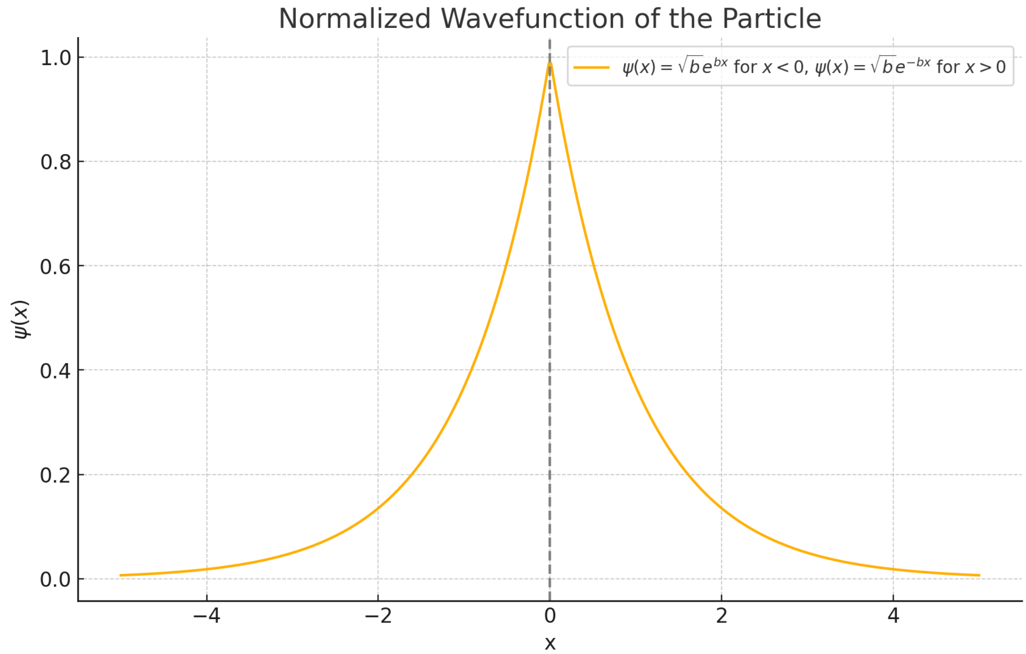

Figure 11: Graph produced by Physics Oracle GPT when answering question 2 [11]

d) Math Solver [12]

Figures 12 and 13 show the pictures produced by the Math Solver GPT. They are similar in style to those produced by Diagrams <Solve Me> (Figures 3-5). Although the GPT correctly solved the problems, these pictures are unclear, smudged and poorly labelled, and do not accurately demonstrate the problems at all.

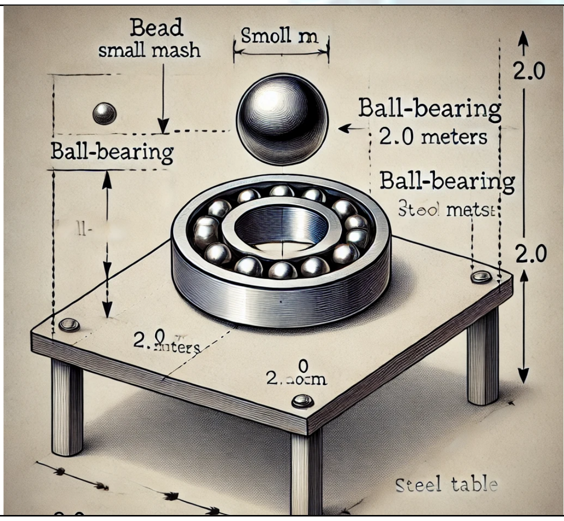

Figure 12: Picture produced by Math Solver GPT when answering question 1

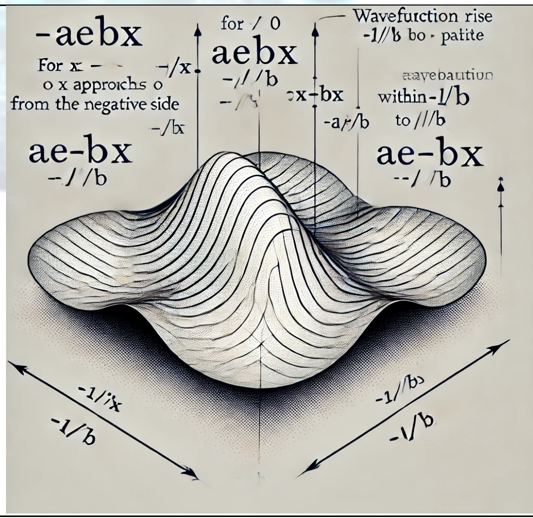

Figure 13: Picture produced by Math Solver GPT when answering question 2

e) Mermaid Chart

Figure 14 breaks down the problem into steps but adds nothing to the physical understanding of the problem. When question 2 was used as a prompt, the GPT created flowchart code (Figure 15) and supposedly, produces said flowchart as well. However, there was an error in rendering the image within ChatGPT so I copied the code into the Mermaid Editor website. There was still an error in producing the flowchart therefore I was forced to conclude that there must have been an error somewhere in the code.

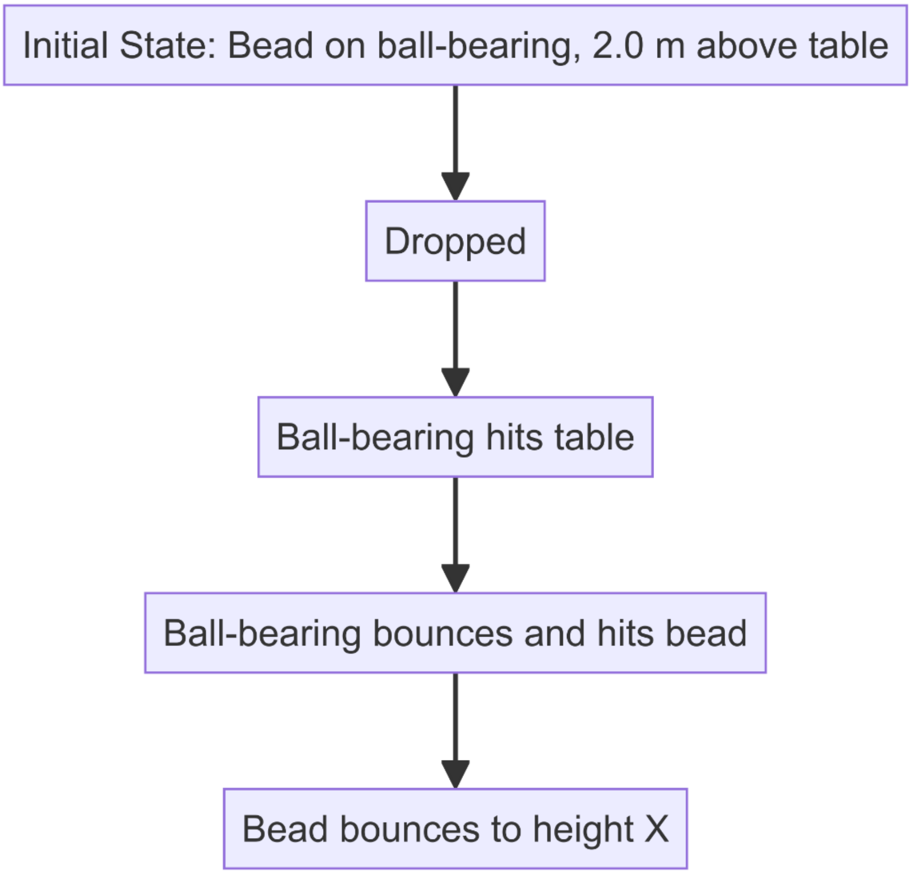

Figure 14: Flowchart produced by Mermaid Charts GPT when asked question 1 [13]

mermaid — Copy code

```
flowchart TD
    A[Wavefunction psi]
    A -->|x < 0| B[psi = A * exp(bx)]
    A -->|x > 0| C[psi = A * exp(-bx)]
```

Figure 15: Code produced by Mermaid Charts GPT when asked question 2 [14]

4. Making my own GPT

I now began to create my own GPT, using my knowledge from experimenting with pre-existing models. My initial model ("Physics Diagram Drawer") aimed to convert text into high-quality diagrams, similar to those in Figures 3, 4, 5 and 12.

> This GPT is designed to assist with solving physics problems by drawing simple, 2-dimensional, monochromatic schematics with singular straight lines, short labels (no more than two words), and no shadows, shading, or blurs. It generates schematics to help explain concepts clearly and directly without performing any calculations. The goal is to provide accurate and minimalistic schematics to support the user's understanding of a physics problem.

Figure 16: Instructions for configuration of 'Physics Diagram Drawer' MyGPT

Despite my best efforts, the pictures were overly complex (see Figure 17): it was impossible to completely remove shading, smudging, 3D elements, and spelling errors.

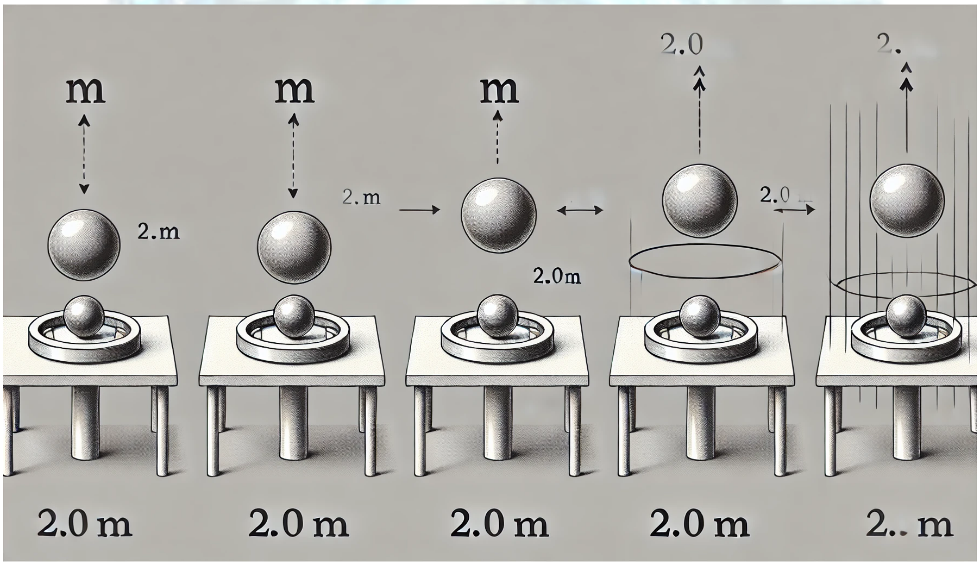

Figure 17: Final effort picture produced by trial GPT 'Physics Diagram Drawer'

I also created the reverse - a diagram-to-text GPT - tested on diagrams from *University Physics with Modern Physics, 15th Edition*. This model generated caption-style explanations for a given diagram. It performed much better than the text-to-diagram GPT, with clear and error-free explanations. There was a minor issue with the GPT describing labels on the graph but this was rectified by clarification of instructions.

Having explored all these multimodal methods and consulted my supervisor, I concluded that text-based images were the clearest, most reliable and simplest format. I began to develop my prototype GPT – The Physualiser.

5. Methodology: Quantifying my findings

An educational chatbot is usually assessed against the self-perceived learning of students using the chatbot with those of a control group not using the chatbot during the same period [15][16]. Unfortunately there can be a novelty effect at play here; initially learning interest increases but wanes as time progresses. This can be due to frustrations if the chatbot lacks fluency or fails to provide satisfactory answers [17]. Furthermore, ethical concerns arise regarding the fair distribution of educational resources as some students may gain an inequitable advantage. Ultimately, this resource would be for student use however, due to the exploratory nature of the research and also the dramatic drop in Durham's student population over the summer, this was not practical. Consequently alternative methods were explored to quantify the effects of the Physualiser.

Audio chatbots can be quantitatively analysed using metrics such as spontaneity, hesitation, degree of reasoning and length & structure of conversation, and these may be transferable to text chatbots [18]. One study defined an 'artificial personality' for the chatbot which involved self-consciousness, humour, purity, IQ, emotional quotient, memory, self-learning and charisma, and measured this [19]. I also considered whether I could use the principles of good teaching: student-faculty contact, cooperation among students, active learning, prompt feedback, time on task, high expectations, respect for diverse talents & ways of learning, to establish a metric with which to quantify the chatbot's efficacy [20]. However, I recognised the potential for self-bias in this assessment. Instead, I decided to rank the diagrams produced by my GPT based on scores I gave them, taking into account four key components: title and labels; neatness and clarity; accuracy; overall presentation. Ultimately, the best metric for a service-oriented chatbot, like the Physualiser, is whether it performs the desired service/task, and so I also measured whether the Physualiser provided correct or incorrect answer to the questions posed.

6. The Physualiser [21]

My aim was to create a GPT that aided problem-solving in 3 steps:

1. **Re-representing** the question (as a text-based diagram)
2. Providing **theory** relevant to solving the question
3. Giving a final **answer** to the problem (often numerical)

Instructions: Physualiser specializes in drawing diagrams for simple kinematics and mechanics problems using ASCII and Unicode art. These diagrams use symbols instead of code or images to visualize the problems. When given a problem, it should break down the scenario into a clear, symbolic representation that helps users understand the mechanics or kinematics involved.

Constraints: Always use ASCII and Unicode characters to represent the diagrams, ensuring the output fits within a 64x32 character grid. Avoid using images or complex visual elements. The diagram should not include the answer to the question, only the information provided in the question. Do not provide links to external sites.
Guidelines:
- Use Unicode box-drawing characters to create clear, visually appealing diagrams.
- Present diagrams in a format that best represents the problem, which may be vertical, horizontal, or another arrangement.
- Ensure each stage of the problem is clearly labelled and easy to differentiate.
- The first result must be the ASCII diagram, followed by relevant theory, and then the working steps including any necessary calculations. Only give the answer when specifically told 'give the answer.'
- Always start the response with the diagram, regardless of any preceding context.
- Ensure that all numerical answers are given to 3 significant figures.

Clarification: If the problem description is unclear or incomplete, ask for more details to ensure an accurate representation.

Personalization: Tailor responses to be educational and supportive, helping users understand the principles of mechanics and kinematics through visual representation.

Special Note: Always draw a diagram using ASCII art/Unicode for every response.

Figure 18: Instructions and details for configuration of Physualiser MyGPT

As is evident from the instructions above, it was sometimes appropriate to reiterate instructions. Initial refinements were made through experimentation with simple kinematics prompts such as 'draw a ball falling from a height'. Subsequently, I turned to my 'Foundations of Physics 1' course which defined 16 key kinematics principles:

1. Vectors
2. Straight Line Motion
3. Motion Under Constant Acceleration
4. Projectile Motion
5. Circular Motion
6. Relative Motion
7. Newton's Laws of Motion
8. Equilibrium & Dynamics

9. Gravitation Potential Energy (GPE) & Elastic Potential Energy (EPE)
10. Work, Kinetic Energy (KE) & Power
11. Dynamics of Circular Motion
12. Types of Forces
13. Centre of Mass
14. Collisions
15. Momentum & Impulse
16. Friction & Fluid Resistance.

I took the first 8 principles and asked the Physualiser 3-5 questions, taken from *University Physics with Modern Physics,* in each area. For these principles, I manually refined and perfected the diagrams by copying the code into TextEditor as a .txt file. I could then go into the diagrams and add/remove symbols as required to make the diagrams clearer. These so-called 'exemplar diagrams' were uploaded to the 'Knowledge' section of the Physualiser's configuration area before the next test I performed. Henceforth the data collected from these first 8 principles is labelled 'in-distribution' data, and data collected from principles 9-16 'out-distribution' data.

a) Does the Physualiser work?

As a control, I asked ChatGPT these same 26 questions with the instruction: *Draw using ASCII art or Unicode and answer the question [question pasted]*
I ranked and rated these diagrams, as well as taking note of whether the question was solved correctly (Figure 19).

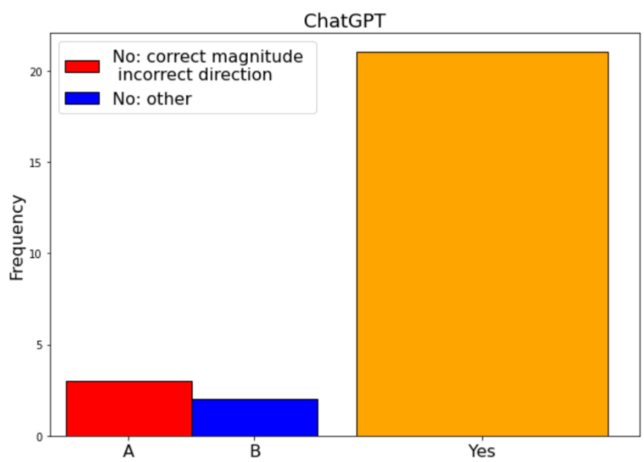

Figure 19: Number of correct and incorrect answers ChatGPT gave when asked kinematics questions

ChatGPT successfully solves the question in the vast majority of cases (81%). Moreover, in 60% of incorrect cases, the error is minor – the direction of the answer is incorrect, despite accurate numerical calculation. Another error involved a solution correct to the nearest whole number, but incorrect due to significant figures preceding in the problem. Again, this is a minor error. Therefore, ChatGPT alone is a fairly reliable tool for checking and answering first year physics problems.

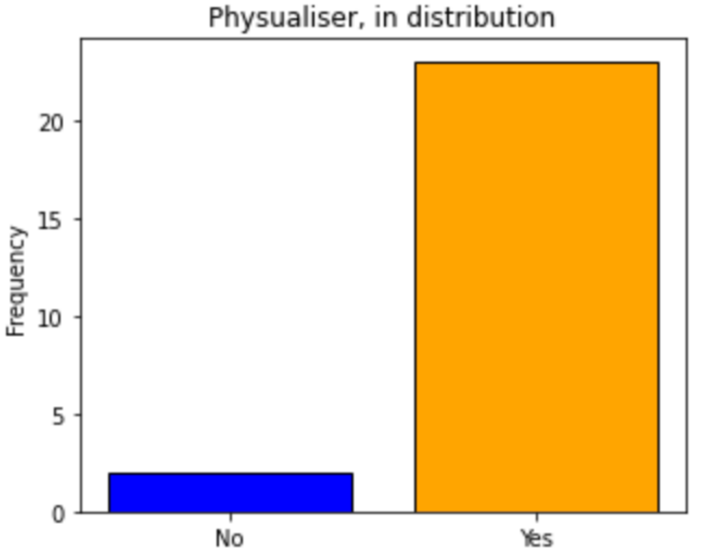

Figure 20: Number of correct and incorrect answers the Physualiser gave when asked kinematics questions (in-distribution)

Figure 20 shows that the Physualiser answered questions with higher accuracy than ChatGPT alone (93% compared to 81%). However there were fewer questions used in this sample (n=24 whereas n=26 for the ChatGPT run). This was due to the time-intensive process of manually perfecting each diagram. Moreover, ChatGPT refused to draw a diagram for the following question citing 'policy restrictions'.

> Superman throws a 1650N boulder at an adversary. What horizontal force must Superman apply to the boulder to give it a horizontal acceleration of 13.6m/s^2?

Figure 21: Kinematics question deemed "too dangerous" to draw a diagram of

Upon further investigation, it transpires that ChatGPT is unable to draw diagrams that may be interpreted as depicting physical harm or violence, even in hypothetical contexts.

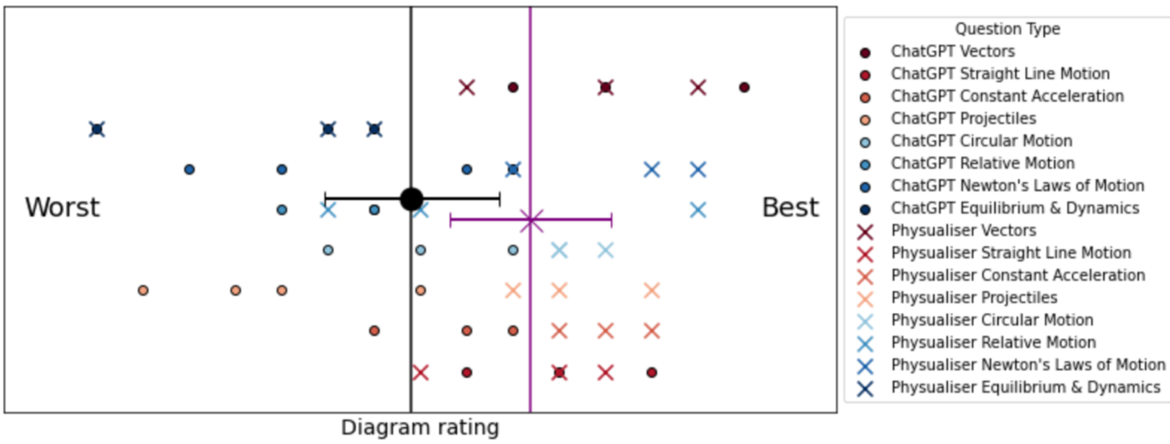

Figure 22: Comparing ChatGPT to Physualiser diagrams

Figure 22 shows the spread of diagram results from the Physualiser and ChatGPT tested on the same questions. The purple line represents the mean and standard deviation of the Physualiser and the black line represents the same for the ChatGPT results. The diagrams produced by the Physualiser score higher on my metrics than those produced by ChatGPT. Thus I was confident that the Physualiser was working as intended.

b) Is the Physualiser flexible?

My next test on the Physualiser was to see how it fared on out-distribution data. I had imported all the exemplar diagrams from the first 8 principles into the Physualiser and now I asked questions relating to the remaining 8 principles (9-16). Again, these 26 questions were taken from *University Physics with Modern Physics*.

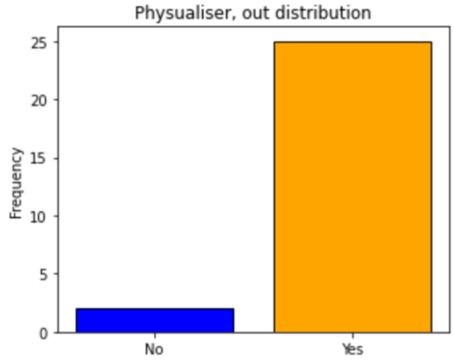

Figure 23: Number of correct and incorrect answers the Physualiser gave when asked kinematics questions (out-distribution)

The out-distribution questions are only slightly less successful than the in-distribution questions (92% vs 93%). The two incorrect responses involved minor errors: one was correct to the nearest whole number (but overall incorrect due to significant figure precedent), and the other only provided one of multiple solutions. This shows that the Physualiser is genuinely fit for purpose and could be easily scaled up and tested further.

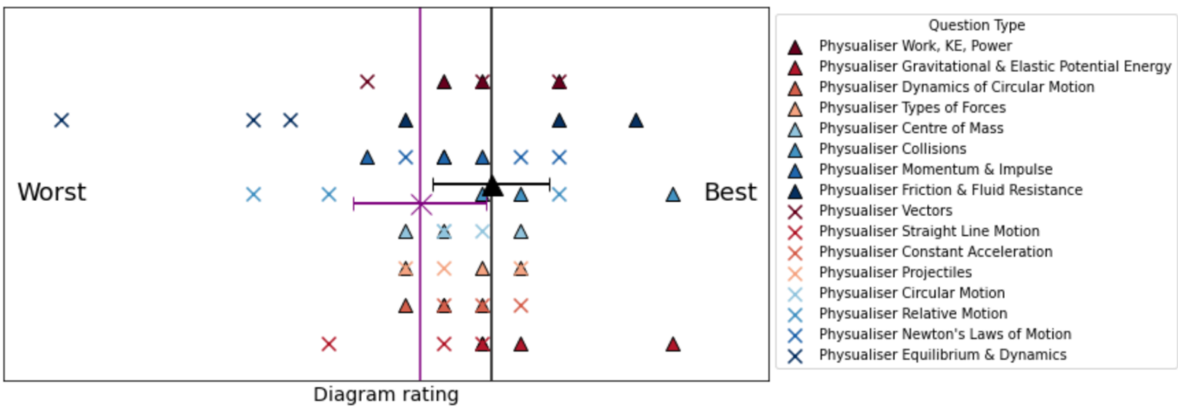

Figure 24: Comparing in-distribution diagrams to out-distribution diagrams, produced by the Physualiser

Figure 24 shows that there is a narrower spread of quality of diagram for the in- and out-distribution data than the ChatGPT and in-distribution data, which was anticipated. The purple cross and lines represent the mean and standard deviation of the ratings of the in-distribution diagrams, while the black triangle and lines represent the same for the out-distribution diagrams. This illustrates that the Physualiser still performs well on questions it has not seen before. Hence, it could be used as a general learning tool, and is not only useful on content it has seen before.

c) Can the Physualiser handle harder physics?

For my final test, I assessed the Physualiser's performance on physics concepts beyond kinematics, specifically quantum mechanics. This topic is on the opposite end of the conceptual understanding spectrum in first year physics. Again, I used the Foundations of Physics 1 course to determine 8 key quantum principles:

1. Wave-Particle Duality
2. Heisenberg's Uncertainty Principle
3. Models of Atoms
4. The Schroedinger Equation
5. Particle in a Box
6. Potential Wells (finite & infinite)
7. Quantum Barriers & Tunnelling
8. The Harmonic Oscillator

And selected three questions from the textbook for each one. These questions were posed to the Physualiser and the output diagram rated.

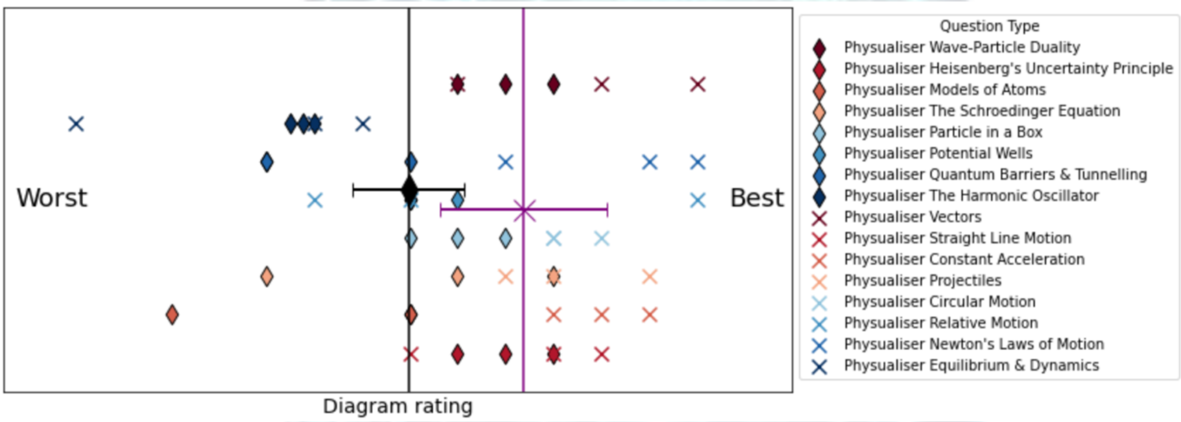

Figure 25: Comparing in-distribution mechanics diagrams to out-distribution quantum mechanics diagrams

This figure shows that the Physualiser performs worse on quantum mechanics questions (black line) than kinematics questions (purple line). However, the overlap of the standard deviations (horizontal lines) shows that this difference is marginal.

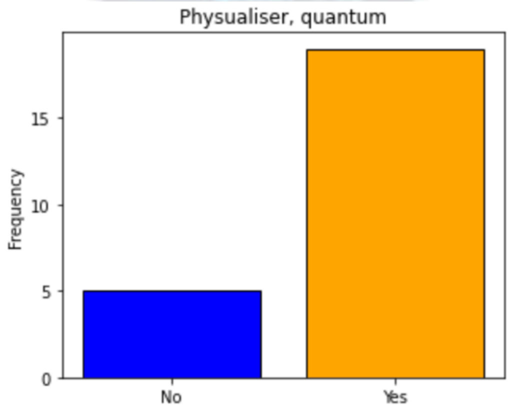

Figure 26: Number of correct and incorrect answers the Physualiser gave when asked quantum mechanics questions

The Physualiser is highly accurate on quantum mechanics questions, with a 79% success rate, although this is lower than for kinematics. Therefore, while the Physualiser is appropriate to use with topics on which it has not been specifically trained, caution is advised.

7. Conclusions

The Physualiser is an effective aid in answering physics questions, can flexibly answer questions outside its knowledge base, and initial tests indicate it can also handle more complex physics concepts. Although it is still a work in progress, the Physualiser has demonstrated the potential capabilities of LLMs and their relevance to accessibility to physics education. I iterated the kinematics process several times and this improved performance. While the slight decrease in success rate is disappointing, I believe with further work this performance could be improved. Moreover, with further refinements and a wider training database, the Physualiser would become an invaluable tool in any physics student's armoury. But, importantly, would provide vital support to those who have previously struggled to access physics.

Future explorations could involve importing the entire undergraduate textbook (*University Physics with Modern Physics*) as 'knowledge' into the Physualiser's configuration. Other options include expanding to adjacent subjects such as Maths, Engineering or Chemistry; integrating into secondary science education; or even higher-level physics study. Furthermore, I hope to test the Physualiser using a group of actual students. Students are away during the summer (when this research was completed) but I aim to continue my work and perform a learning intervention during term time. Overall, the Physualiser provides a useful resource for visualising kinematics problems in undergraduate first year physics, as well as assisting with other physics topics, however, there is scope for significant improvement in performance through further investigation and expansion.

A NOTE *on citations*: I have tried to cite specific ChatGPT/GPT chats and conversations, where possible. However, ChatGPT does not yet support sharing conversations that contain images. In these cases, I have, instead, cited the GPT itself.

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