Daria Wójcik
Alicja Niewiadomska
Maciej Paszyński

CAN ARTIFICIAL INTELLIGENCE PREDICT A TSUNAMI?

Abstract *In this article, we build a model for tsunami simulation based on physics-informed neural networks and the finite difference method. We then check how the numerical results obtained using these two methods differ from each other. Assuming that the finite difference method gives accurate results, we estimate the error resulting from the use of physics-informed neural networks. We compare this estimate with surveys conducted among computer science students in order to assess the level of public trust among specialists in the numerical results obtained using artificial intelligence tools. In particular, we assess how reliable tsunami predictions obtained using physics-informed neural networks are and what the public perception of the reliability of such predictions is.*

Keywords physics informed neural networks, tsunami simulations, artificial intelligence, finite difference method

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1. Introduction

Physics Informed Neural Networks (PINNs) [12] and Variational Physics Informed Neural Networks (VPINNs) [6] are modern methods for training neural network solutions of partial differential equations (PDEs). PINNs and VPINNs employ the residual loss function during the training procedure. PINNs employ a strong loss function and use collocation points during training, while VPINNs utilize weak residuals with integration using selected test functions. The PINN is a neural network that learns the solution to the differential equation. NNs are universal function approximators. We use fully-connected neural networks with 3 inputs (x, y, and t) and a single output u, the water level at that space-time point.

In PINNs and (R)VPINNs, the loss is typically comprised of several components; in addition to the norm of the residual, it encompasses penalty terms corresponding to boundary and/or initial conditions. As they may differ significantly in scale and importance, special care is required to ensure that all components are properly treated during training. One viable approach is to construct the loss function as a weighted sum, where the weights are automatically scaled [1]. An alternative is to treat PINN training as a multi-objective optimization task, as in the Jacobian descent method [11]. Recently, PINNs have been applied to solving shallow-water equations [9, 10], including modeling a tsunami wave [2, 7]. However, these works focus on a relatively small region and do not allow for predicting the global impact of such an event. Of these two, only [7] presents 2D results, although it has flat bathymetry. In [3], PINNs have been used to solve shallow-water equations in spherical geometry. Achieving acceptable accuracy on reasonable time scales requires splitting the temporal domain into subintervals and training multiple separate PINNs connected by initial conditions. We are not aware of any shallow-water equation simulations employing Variational PINNs.

We develop a model for tsunami simulation based on Physics Informed Neural Networks and the Finite Difference Method. We then investigate the degree to which the numerical results obtained from these two methods differ. We estimate the error that arises from the use of PINNs. We compare this assumption with surveys of computer science students to assess the general confidence in numerical results obtained with AI tools. Specifically, we assess how reliable tsunami predictions obtained with physics-informed neural networks are and how the public evaluates the reliability of these predictions.

2. Modeling of tsunami with Physics Informed Neural Networks and Finite Difference Method

We will start with the following wave equation approximation of the shallow water equations, and we will improve and augment it with tides, winds, variations in the acceleration due to gravitational forces, and the oblate spheroid geometry of the Earth surface.

The wave equation is derived from the shallow water theory equations. Specifically, it employs the nonlinear wave equation as presented in the work of [8]. The form of the equation is given by:

$$\frac{d^2u(x,y,t)}{dt^2} - \nabla\left(g(u(x,y,t) - z(x,y))\nabla u(x,y,t)\right) = 0 \tag{1}$$

where g represents the acceleration due to gravity and $z(x,y)$ is the seabed topography. After expanding it using the product rule, for a two-dimensional problem, it becomes:

$$\frac{d^2u}{dt^2} - g\left(\frac{\partial}{\partial x}\left((u-z)\frac{\partial u}{\partial x}\right) + \frac{\partial}{\partial y}\left((u-z)\frac{\partial u}{\partial y}\right)\right) = 0 \tag{2}$$

The contributions from the x and y derivatives can be combined as follows:

$$\frac{d^2u}{dt^2} - g\left((u-z)\left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}\right) + \frac{\partial(u-z)}{\partial x}\frac{\partial u}{\partial x} + \frac{\partial(u-z)}{\partial y}\frac{\partial u}{\partial y}\right) = 0 \tag{3}$$

The outcome is the second-order nonlinear PDE that describes wave propagation. Here z is the topography of the seabed, and g is a gravitational acceleration constant. The initial condition and the boundary conditions were combined with the residual loss using scalar linearization.

Figure 1 presents exemplary initial conditions for a given set of parameters.

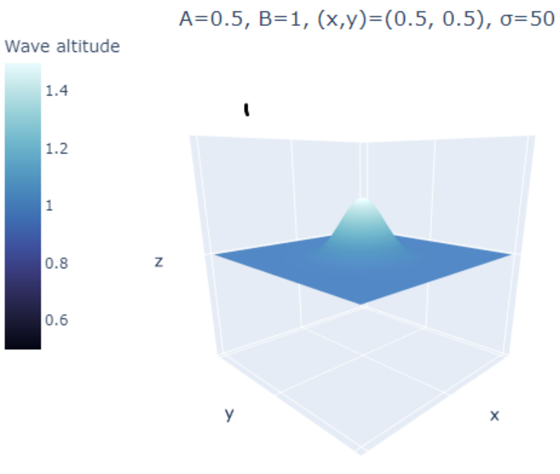

Figure 1. Initial conditions

The boundary conditions for the tsunami wave equation are defined using Neumann conditions, which specify the derivative of the wave height at the boundaries.

These conditions are expressed as:

$$\frac{\partial u}{\partial n} = 0 \quad \text{on} \quad \partial\Omega \tag{4}$$

where $\partial\Omega$ is the boundary of the domain Ω, and $\frac{\partial u}{\partial n}$ represents the normal derivative of the wave height u. This condition ensures that there is no flux of the wave height across the boundary, effectively simulating a reflective barrier.

The seabed topography is represented using triangular mesh data, depicting the topography of the Valparaiso coastline region in Chile. The data come from the Giant Metrewave Radio Telescope (GMRT), which is public and accessible online[1]. The visualization of the topographic data is presented in Figure 2.

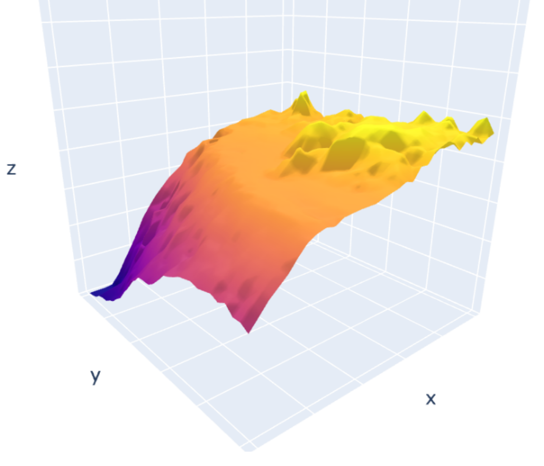

Figure 2. Seabed topography visualization

2.1. Finite Difference Method for the Tsunami Problem

In this section, the finite difference method for modeling tsunami waves is derived. By discretizing the continuous partial differential equation, the continuous model is transformed into a system of algebraic equations that can be solved numerically, enabling the simulation of tsunami wave propagation over time. For the modelling of the tsunami with FDM the residual form of the equation 3 is used:

$$\frac{d^2u}{dt^2} - g\left((u-z)\left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}\right) + \frac{\partial(u-z)}{\partial x}\frac{\partial u}{\partial x} + \frac{\partial(u-z)}{\partial y}\frac{\partial u}{\partial y}\right) = 0 \tag{5}$$

[1]https://www.gmrt.org/GMRTMapTool/

The explicit Euler time integration scheme is employed for time discretization. First, the approximation of the second-order time derivative $\frac{d^2u}{dt^2}$ using a central difference approximation is calculated:

$$\frac{d^2u}{dt^2} \approx \frac{u_{t+1} - 2u_t + u_{t-1}}{\Delta t^2} \tag{6}$$

where u_i represents the value of u at the i-th time step, and Δt is the time step size.

$$\frac{u_{t+1} - 2u_t + u_{t-1}}{\Delta t^2} = g\left((u-z)\left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}\right) + \frac{\partial(u-z)}{\partial x}\frac{\partial u}{\partial x} + \frac{\partial(u-z)}{\partial y}\frac{\partial u}{\partial y}\right) \tag{7}$$

where z denotes the seabed. Next, to obtain equation for u_{t+1} the equation is rearranged to:

$$u_{t+1} = u_t + u_t - u_{t-1} + \Delta t^2 g\left((u-z)\left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}\right) + \frac{\partial(u-z)}{\partial x}\frac{\partial u}{\partial x} + \frac{\partial(u-z)}{\partial y}\frac{\partial u}{\partial y}\right) \tag{8}$$

The following expressions are used for discretizing the second and first derivatives with respect to x and y. We start from the second derivative with respect to x and y,

$$\frac{\partial^2 u}{\partial x^2} \approx \frac{u_{i+1,j} - 2u_{i,j} + u_{i-1,j}}{h^2} \tag{9}$$

$$\frac{\partial^2 u}{\partial y^2} \approx \frac{u_{i,j+1} - 2u_{i,j} + u_{i,j-1}}{h^2} \tag{10}$$

the first derivative of u with respect to x and y,

$$\frac{\partial u}{\partial x} \approx \frac{u_{i+1,j} - u_{i-1,j}}{2h} \tag{11}$$

$$\frac{\partial u}{\partial y} \approx \frac{u_{i,j+1} - u_{i,j-1}}{2h} \tag{12}$$

and finally, the first derivative of z with respect to x and y,

$$\frac{\partial z}{\partial x} \approx \frac{z_{i+1,j} - z_{i-1,j}}{2h} \tag{13}$$

$$\frac{\partial z}{\partial y} \approx \frac{z_{i,j+1} - z_{i,j-1}}{2h} \tag{14}$$

We substitute into the wave equation

$$u_{t+1} = u_t + u_t - u_{t-1} + \Delta t^2 \cdot g \cdot \tag{15}$$

$$\left((u_{i,j} - z_{i,j})\left(\frac{u_{i+1,j} - 2u_{i,j} + u_{i-1,j}}{h^2} + \frac{u_{i,j+1} - 2u_{i,j} + u_{i,j-1}}{h^2}\right)\right. \tag{16}$$

$$+\left(\frac{u_{i+1,j} - u_{i-1,j}}{2h}\right)^2 + \left(\frac{u_{i,j+1} - u_{i,j-1}}{2h}\right)^2 - \left(\frac{z_{i+1,j} - z_{i-1,j}}{2h}\right) \tag{17}$$

$$\left.\left(\frac{u_{i+1,j} - u_{i-1,j}}{2h}\right) - \left(\frac{z_{i,j+1} - z_{i,j-1}}{2h}\right)\left(\frac{u_{i,j+1} - u_{i,j-1}}{2h}\right)\right) \tag{18}$$

This equation is used for simulating wave propagation using the Finite Difference Method. By iterating over these equations for each time step and spatial point, the dynamic evolution of the wave over time is modeled. We employ the Neumann boundary conditions

$$\frac{\partial u}{\partial n} = 0 \quad \text{on the boundary} \tag{19}$$

where $\frac{\partial u}{\partial n}$ represents the derivative of u in the direction normal to the boundary.

In the discrete form, this condition can be approximated as:

$$\frac{u_{1,j} - u_{0,j}}{h} = 0 \quad \text{or} \quad u_{1,j} = u_{0,j} \tag{20}$$

$$\frac{u_{N,j} - u_{N-1,j}}{h} = 0 \quad \text{or} \quad u_{N,j} = u_{N-1,j} \tag{21}$$

$$\frac{u_{i,1} - u_{i,0}}{h} = 0 \quad \text{or} \quad u_{i,1} = u_{i,0} \tag{22}$$

$$\frac{u_{i,M} - u_{i,M-1}}{h} = 0 \quad \text{or} \quad u_{i,M} = u_{i,M-1} \tag{23}$$

where i and j are indices representing the spatial grid points, N is the total number of grid points in the x-direction, and M is the total number of grid points in the y-direction.

These boundary conditions ensure that the wave does not pass through the domain boundaries, effectively reflecting back into the domain, which is essential for the accurate simulation of tsunami waves. The initial condition is directly used by Finite Difference Methods as the initial step of the simulation.

For the solution of system of linear equations processed by the Finite Difference Method we have employed the MUMPS solver [4, 5].

2.2. Physics Informed Neural Network for the Tsunami Problem

For the modelling of the tsunami with PINN the residual form of the previously introduced equation 3 is used:

$$\frac{d^2u}{dt^2} - g\left((u-z)\left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}\right) + \left(\frac{\partial u}{\partial x}\right)^2 + \left(\frac{\partial u}{\partial y}\right)^2 - \frac{\partial z}{\partial x}\frac{\partial u}{\partial x} - \frac{\partial z}{\partial y}\frac{\partial u}{\partial y}\right) = 0 \tag{24}$$

The solution is represented by the neural network:

$$u(x,y,t) = PINN(x,y,t) = W_n\sigma\left(W^{n-1}\sigma(...\sigma(W^1\begin{bmatrix} x \\ y \\ t \end{bmatrix} + b^1)... + b^{n-1}\right) + b^n \tag{25}$$

where $u(x,y,t)$ is approximated as a function of the inputs x, y, and t through a neural network. The network consists of multiple layers, each defined by a weight matrix W^k

and a bias vector b^k, with non-linear transformations applied at each layer using the hyperbolic tangent activation function σ.

Based on the Equation (3), the loss components can be determined:

- **Initial Condition Loss**:

$$Loss_{initial} = \sum_{i=1}^{N_{initial}} |u(x_i, y_i, 0) - u_0(x_i, y_i)|^2$$

where u_0 is determined by the initial equation

- **Boundary Condition Loss**:

$$Loss_{boundary} = \sum_{i=1}^{N_{\text{boundary}}} \left| \frac{\partial u}{\partial \boldsymbol{n}}(x_i, y_i, t_i) \right|^2$$

This represents the Neumann boundary condition, where the derivative of u normal to the boundary is considered.

- **Residual Loss**:

$$Loss_{residual} = \sum_{i=1}^{N_{residual}} \left| \frac{d^2 u}{dt^2} - \nabla\left(g(u - z)\nabla u\right) \right|^2$$

This ensures that the solution satisfies the underlying differential equation.

The total loss is defined as:

$$Loss = Loss_{initial} + Loss_{boundary} + Loss_{residual}$$

The PINN receives x, y, t as input variables. Neural Network processes these inputs to predict the output u (the solution to the PDE). By utilizing automatic differentiation, the necessary derivatives for the residual equation are calculated, and these derivatives are then used to compute the final loss.

3. Comparison of Physics Informed Neural Networks and Finite Difference Method

The Finite Difference Method simulation was run as a baseline to compare with Physics-Informed Neural Networks. The experiment was run with a time step of 0.001 over 250 epochs. A grid of size 128 × 128 was used to discretize the spatial domain [0,1] × [0,1] in both dimensions. The results are presented from a side view in Figure 3.

The Figure 4 also provides a comparison between the FDM and the PINN models for simulating tsunami wave propagation over coastal topography. In the early stages of the simulation, the PINN closely follows the FDM results, showing that it has effectively learned the initial condition. However, as the simulation progresses, the differences between the models become more evident, especially in the wave's outer regions.

These emerging differences highlight that while the PINN performs well initially, it struggles to maintain accuracy as the wave propagates further. The most significant deviations occur in the later stages, suggesting that the PINN model may need further refinement, particularly in its treatment of boundary conditions and its ability to accurately model wave dynamics over extended periods.

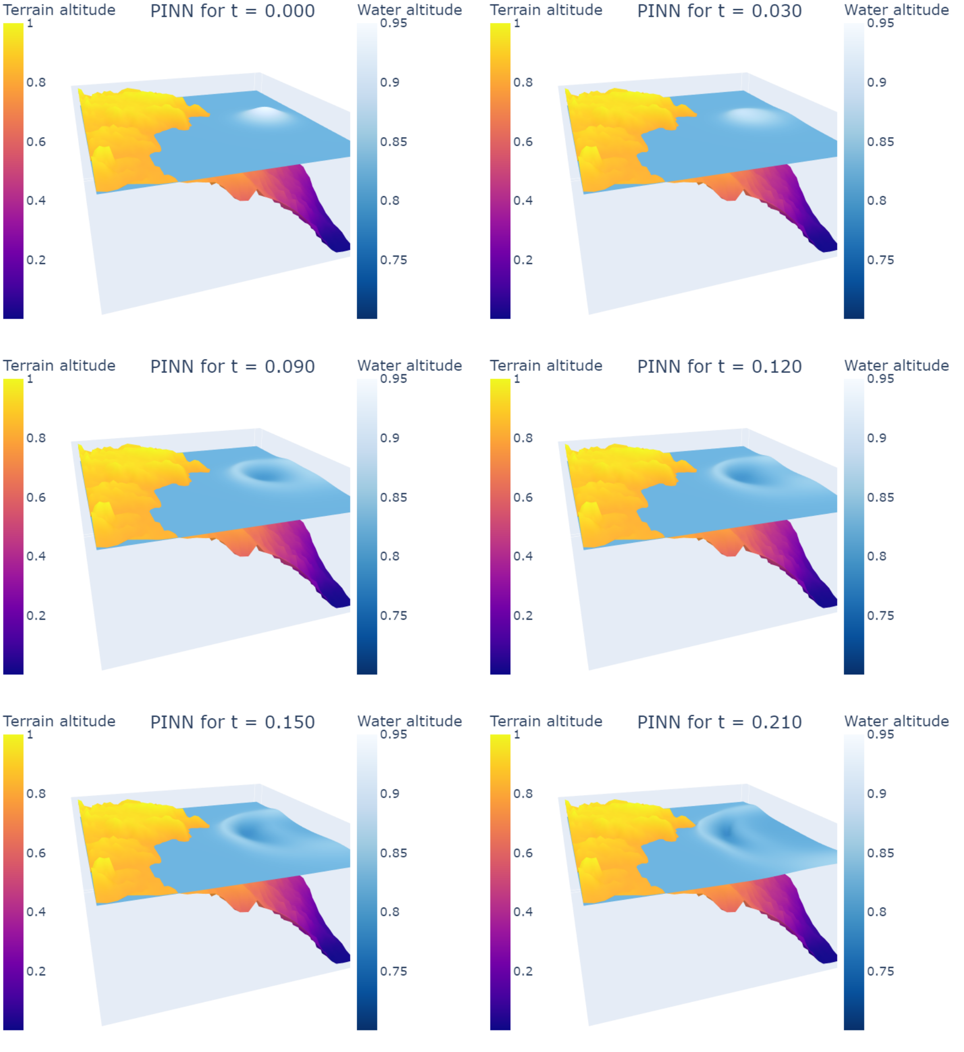

Figure 3. PINN simulation results (side view)

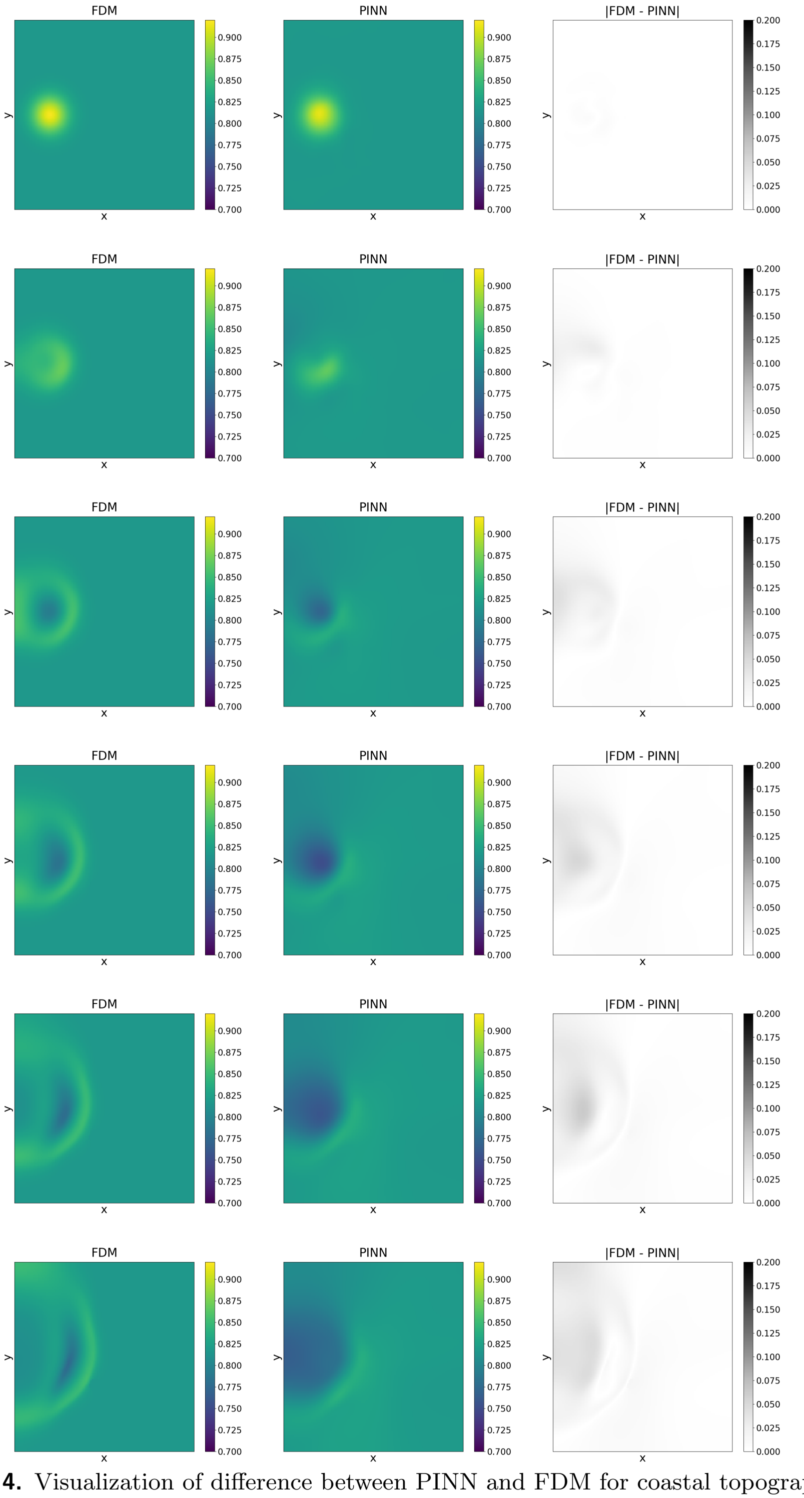

Figure 4. Visualization of difference between PINN and FDM for coastal topography

4. Survey among computer science students

Can AI tsunami predictions be trusted? To address the question, we conducted a study among 176 first-cycle undergraduate students in computer science at AGH University in Krakow ($N = 118$) and applied computer science at Jagiellonian University in Krakow ($N = 58$). We were interested in how AI-driven computing is perceived by todays' students and future experts and professionals who may perform numerical simulations in various areas, including seismic and ocean simulations. In the study, we applied an online survey and hosted it via MS Forms. The survey link was distributed to students at both universities by the instructors of the selected courses. The sample was dominated by male students (81%)[2].

The average age was 21 years. The third year students slightly dominated the Bachelor's degree programs over the last six semesters (first year students – 27%, second year students – 24%, third year students – 49%)[3]. One third of the participants in the study program took courses that introduced how to use AI in engineering or scientific computing (32%). Additionally, every five students can apply methods for verifying AI computations (19%) or regularly use AI-powered engineering software for engineering or scientific computing (19%).

During the research, the students were asked several questions about AI[4]. Some of these referred to assessing the credibility of computations performed by AI in specific scenarios, such as weather forecasting, verifying the durability of residential buildings, car construction, and testing the resistance of aircraft. The findings suggest a clear lack of trust in AI for life-critical applications in the presented scenarios (see Figure 5).

The general trend we observe is that, as AI takes over more of the decision-making process in physical durability verification, concerns are growing that any errors could have more serious consequences for humans. Of the four scenarios, the highest level of confidence in AI calculations is found in tsunami prediction. Here, the AI system functions as an early warning tool. This suggests that the acceptance of AI results is highest when the possible consequences of an error do not directly threaten the respondent's life.

[2]These proportions are consistent with the general trend of significantly lower female participation in STEM, which is observed in both scientific work and studies in Poland and around the world. See: https://unesdoc.unesco.org/ark:/48223/pf0000377456/PDF/377456eng.pdf.multi.page=1&zoom=auto,-16,842

[3]in applied computer studies at Jagiellonian University in Krakow, while engineer ing degree programs (computer studies at AGH University in Krakow) were evaluated over the last seven semesters. For the purposes of the analysis, the study years were categorized as follows: the first year includes the first and second semesters; the second year includes the third and fourth semesters; and the third year includes the fifth, sixth, and seventh semesters.

[4]See also the more detailed findings from a larger and more diverse sample: Tomasz Służalec, Daria Wójcik, Carlos Uriarteb, Marcin Łoś, Anna Paszyńska, Maciej Paszyński. *Reliable Physics-Informed Neural Networks: Can we trust AI-generated numerical simulations?* submitted to **Journal of Computational Science**

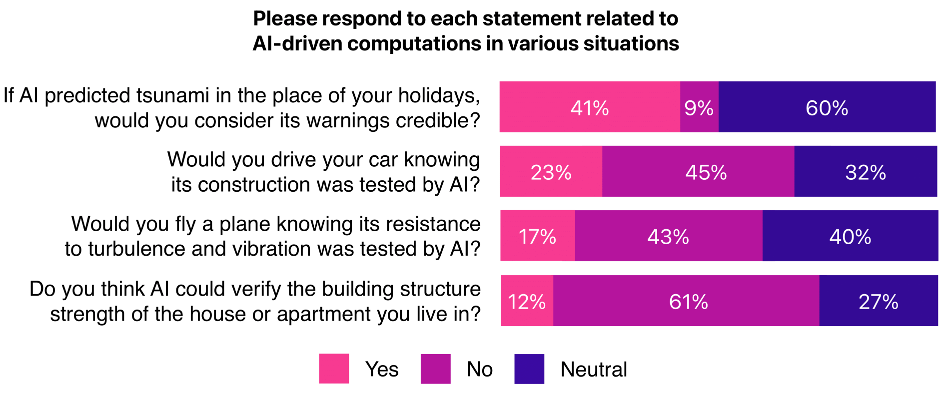

Figure 5. Credibility assessment of AI-driven computations in various contexts ($N = 176$)

Students' trust in AI numerical simulations to predict tsunamis varies significantly according to their individual traits related to knowledge and experience of AI (see Figure 5).

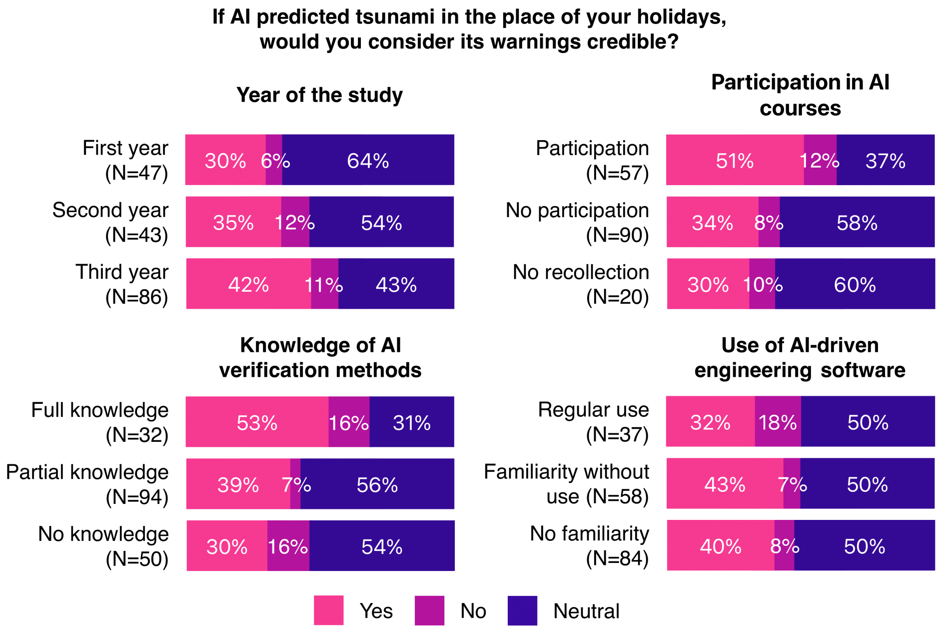

Figure 6. Credibility of AI-driven computations for tsunami prediction versus participation in the AI course, the year of the study, the usage of verification methods applied to AI computations, and the usage of AI-powered computational software

Higher years of study and participation in an AI course within a study program that introduces the use of AI in engineering or scientific computing increase students' trust in AI-driven computations to predict tsunamis. However, trust based on theoretical knowledge may result from overly optimistic expectations or imagination regarding the possibilities of AI, which can create a positive perception of AI and its abilities. This perspective and declared trust are informed by practical knowledge and experience. Trust in AI increases with the ability to verify AI-generated computations. A lack of this ability primarily leads to uncertainty in assessing the credibility of AI-generated tsunami warnings rather than dismissing them outright. The same applies to experience in using AI-driven engineering software. The less familiar one is with such software, the more likely one is to trust AI calculations for predicting tsunamis. Students who regularly use AI-supported software are less likely to assess AI computations as credible, suggesting that experience with AI in performing numerical simulations increases caution and skepticism regarding its absolute reliability in critical situations.

Regardless of their individual traits, the students were asked to justify their choices when declaring trust in AI's ability to predict tsunamis. Three main themes emerged from the gathered data. The first refers to logic and belief in numbers. This type of trust in AI-driven computational tools used to predict tsunamis embraces arguments of competence, including the belief that AI has advantages over traditional models or human intuition in tasks involving the analysis of seismic and oceanic patterns. AI is perceived as an advanced analytical or mathematical tool, which gives it an air of objectivity: 'AI models are tailored to such applications' or 'it's still math'. It is also highlighted that AI operates on numerous factors, large databases, and historical data, which enhance its analytical capabilities; however, it is not 'a magical prophecy'. The other two types of justification are based on the precautionary principle. On one hand, there are arguments about consequences: even if an alert is not perceived as credible, it is worth taking it into consideration, as the cost of a false warning (e.g., shortened holidays or evacuation) is lower than the cost of ignoring a warning (e.g., losing one's life). AI predictions should therefore form the basis for action rather than be considered absolute, proven truths. On the other hand, there are arguments for control: AI needs to be embedded within the remit of relevant experts and be transparent. These two components are key to trusting AI numerical simulations performed to predict tsunamis. Students assume that the model has been sufficiently verified by human experts and that it employs tested computational models, as it was permitted to warn individuals about the tsunami.

5. Conclusions

So, can AI-driven tsunami predictions be trusted? This exploratory study examines how students perceive the role of AI in tsunami prediction. While trust is readily declared at the level of theoretical knowledge and the expectations based on it, students exhibit a higher level of criticism and caution when confronted with experience and the use of practical tools. In the scenario detailed in the study (AI predicts tsunami), trust is based not only on the power of the algorithms and AI but also on the prevailing imperative of risk minimization and the need for human (expert) oversight of AI.

On the other hand, the Large Language Models (LLMs) can generate computational codes that employ either the Finite Difference Method or Physics Informed Neural Networks to simulate tsunamis. They utilize the already available knowledge or algorithms and can perform the same work as can be done by a skilled programmer. They will, however, not propose new computational algorithms; thus, the reliability of LLM predictions is related to the reliability of state-of-the-art algorithms.

From the computational science perspective, as we can see from the presented comparison, Physics Informed Neural Networks differ from Finite Difference Simulations, and there is a need to develop additional algorithms and methods to increase the reliability of numerical simulations performed by these methods.

6. Tsunami simulational code

The python code for running tsunami simulations at the Valparaiso seashore of Chile is available at https://github.com/alicenoknow/tsunami_pinn

This code has been created as an integral part of the Master Thesis of Alicja Niewiadomska entitled "Modeling of tsunami caused by Earthquake at the seashore of Chile with Physics Informed Neural Network (PINN)".

7. Appendix – students answers

In this appendix we present a collection of students answers to the following question: If AI predicted a tsunami in the place where you are on vacation, would you consider these warnings credible?

1. I believe that, with some lead time, tsunami prediction can be carried out with almost perfect accuracy, even considering AI's shortcomings.
2. Yes, credible, because a warning is always worth paying attention to. I believe AI information always follows from something.
3. If an advanced AI system warned about a tsunami, and if that AI were at all reliable, I would evacuate.
4. I think that at the current stage of AI development and available data, such predictions can be considered reliable.
5. If I even have slightly unreliable indications that something bad might happen, I prefer to err on the side of caution.
6. Prudence.
7. Someone had to create the software that calculates this, and AI had to take some information into account, but I would still listen to human opinions as well.

8. In my opinion, AI has analyzed quite a lot of information about tsunamis, so it can accurately predict this situation.
9. AI is a highly advanced statistical model based on historical data. If AI has access to readings, e.g., from seismographs, then based on historical data analysis it can predict the formation of a tsunami.
10. AI can take many factors into account more efficiently, relying on previous events rather than, for example, intuition.
11. AI also gathers information from the internet and experts.
12. Human life is not worth the risk.
13. In my opinion, AI can analyze large datasets far better. For repetitive weather phenomena, AI can more easily estimate the likelihood of similar events based on historical data.
14. I think that in a critical situation, I would prefer to be cautious and trust AI forecasts, as my safety is more important than my vacation.
15. Not so much credible, but I would follow it because even a small chance of a natural disaster is enough to evacuate.
16. It depends how we understand AI - if it's something like ChatGPT, then no, but a tool for predicting tsunamis and other events based on AI and concrete collected data - yes.
17. I assume that the process by which AI predicts this event would be previously verified by experts and deemed sufficiently accurate.
18. Tsunami prediction has been well described and studied for a long time, which gives AI models a lot of data, so they can predict with high accuracy.
19. Assuming that some expert, after entering reliable data, obtained such a simulation result, I see no reason why predictions should be less accurate than those made without AI.
20. Weather forecasts also rely on probabilistic models, so I would also consider such AI-based predictions plausible.
21. It's a warning based on data, so I would probably be concerned.
22. If it's a specialized network, then it's pure data analysis.
23. Not 100% credible, but I wouldn't dismiss it.
24. Better to run away just in case - there's a chance it's right, and you only live once.
25. Well, it's better to be cautious.
26. Even if it turned out to be unreliable, I would consider it appropriate to remain cautious.
27. Often such projects, especially those concerning natural disasters, would likely be supported by the government, so they would have to be fairly reliable.
28. A specialized weather-forecasting model could predict future weather events with fairly high precision.

29. If a model were created that would warn earlier about a potential tsunami than existing non-AI solutions, I would definitely trust it in the case of a tsunami alarm - but not in the opposite situation where AI says there is no danger while other infrastructure warns of an incoming wave.
30. Such a risk should not be ignored, even if I didn't fully trust the model.
31. It would make me check information on the topic.
32. I understand we're talking about models trained on good tsunami data under specialists' supervision, not LMs to which I simply ask "Will there be a tsunami?". In that case, my trust would not differ much from trust in an expert who calculated it manually. I suspect a good model could find even more correlations between data than a human.
33. Because AI can process various data better than humans, and despite computational errors, I believe a good model will better assess risks.
34. I assume the models are trained under the guidance of top specialists in the field and operate far better than standard algorithms, including heuristic ones. However, I would still exercise considerable caution in trusting models, especially on issues such as structural stability and durability.
35. As long as we treat ‱AI" as a tool rather than an infallible oracle, it does not differ significantly from traditional models - it's still mathematics.
36. Better to be cautious; I'm not sure whether AI is right, but it would be foolish to risk it, so I would probably leave.
37. Better be safe than sorry.
38. I think that a model trained to predict tsunamis, if it were deployed, would also be reliable; people need guidance, and I'm not a specialist myself.
39. I don't want to take risks - if there is even a small chance that the warning is true, I prefer to take it seriously and take precautions.
40. If it were allowed to issue warnings, I assume it would be reliable enough to trust.
41. Environmental simulation models seem fairly advanced.
42. If such information were somehow confirmed by experts. It's not like suddenly I'd feel threatened – there would need to be confirmation.
43. This is such a critical area of activity that I trust how the AI was implemented and supervised, and that there is human oversight.
44. It would be good to know how reliable previous predictions were.
45. In this situation, the negative consequences of an AI error are minimal. I assume AI calculations are correct in 99% of cases, so I have no problem accepting a warning generated by AI. Problems arise when AI analysis is the only guarantee of safety.
46. I would be skeptical of the results themselves, but a cautious person always protects themselves.
47. The result would likely be based on some evidence; I would make sure it is possible.

48. I don't trust AI as much as experts, but if such signals appeared, they should not be ignored.
49. AI does not make human errors; the only things that matter are the input data and how it was trained. A well-trained model will perform better in such computational tasks.
50. AI performed the data analysis, so it can predict a tsunami.
51. If this resulted from a simulation, it's better to be careful. I assume that some experts supervise such a system and that it was properly built.
52. As long as the results were confirmed in some way by specialists (i.e., not replacing them with AI but supporting their work), then yes - I would consider the warnings justified.
53. Artificial intelligence has access to huge datasets and can analyze weather or seismic changes faster than humans.
54. The situation is quite similar to Pascal's wager.
55. In the case of threats, better be safe than sorry, and if AI thinks something may happen, there is probably something to it, and it's good to be preventive.
56. I assume that people working in alert centers and similar institutions are responsible enough not to cause panic and that they carefully choose and use different computational models, including machine-learning ones.
57. I rarely encounter AI that makes mistakes, and it's better not to risk it – if AI came to such conclusions, then there's probably something to it.
58. I know that neural networks can predict weather more effectively than much more computationally expensive physical models, so this seems similar.
59. A tsunami depends on many factors; the vector of properties is wide. AI doesn't care if the weather was nice or cloudy - it just looks at its inputs and decides whether these are tsunami - conducive factors or not.
60. I would consider it credible, but I would also listen to the opinions of experts and specialists in this field to be more certain about the events.
61. Only if the predictions were sequentially verified by an expert.
62. I think that in this situation, I would definitely want to know experts' opinions as well, but I would not ignore such warnings.
63. If I considered the specific model used in this case reliable, then yes.
64. A tsunami is a significant threat, and some percentage chance - even if predicted by AI - could prompt me to evacuate. Of course, I would prefer for an expert to support these predictions.
65. If the model were trained to predict this (only this type of) phenomenon based on data from previous tsunamis, I could consider the warnings valid.
66. Tsunami modeling is mainly based on data extrapolation; AI models are well suited for such applications.
67. AI relies on historical data if trained that way. If a tsunami occurred under similar conditions previously, there is a chance it could happen again.

68. If, for some reason, the data allowed calculating a probability higher than minimal, it should not be ignored. These systems specialize in specific tasks - in this case, detecting tsunami threats.
69. It's better not to ignore a potential threat.

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Affiliations

Daria Wójcik
AGH University of Science and Technology, Faculty of Computer Sciences, Krakow, Poland, e-mail: dwojcik@agh.edu.pl

Alicja Niewiadomska
AGH University of Science and Technology, Faculty of Computer Sciences, Krakow, Poland, e-mail: aniewiadomsk@student.agh.edu.pl (current email: alicja.b.niewiadomska@gmail.com)

Maciej Paszyński
AGH University of Science and Technology, Faculty of Computer Sciences, Krakow, Poland, e-mail: paszynsk@agh.edu.pl

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