#### Research on Energy Transition, Digitalisation and Cyber security

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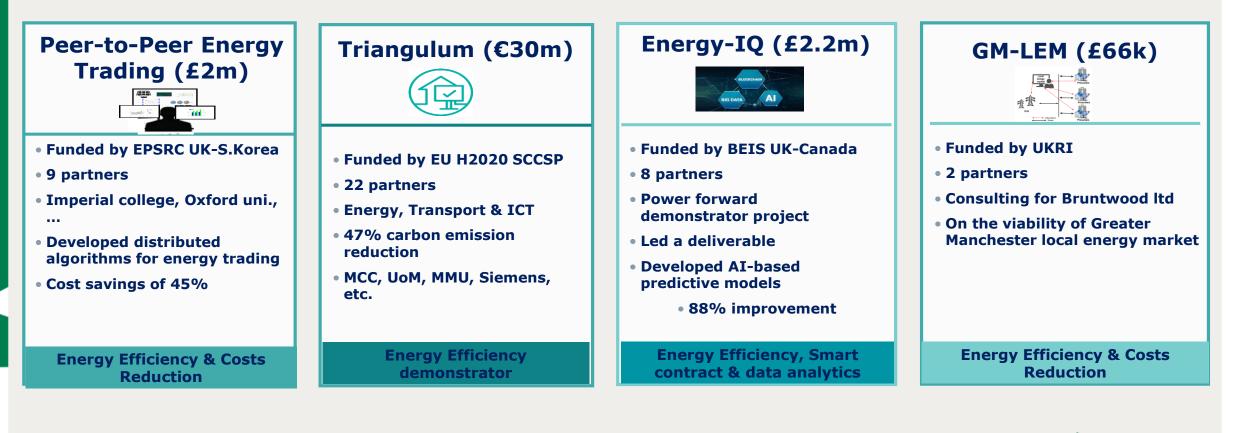




Next Generation Network



# My research in AI, Blockchain & Energy





# My Research in Al, Blockchain & Energy





- Funded by EPSRC SuperGen Network
- Travel grant for an intelligent auction-based energy trading
- AI and blockchain in energy network

Energy Efficiency & Costs Reduction Interlinked Computing (£58k)

- Funded by NWPST
- 4 investigators
- Effect of cobbled systems ( systems of systems)
- Security implication of cobbled system
- Smartgrid case study
- UoM, MMU, Lancaster.

**Energy Network, Security** 



- KTP Funded by Innovate UK
- With Badger Energy
- To develop AI & blockchain secure smart EV charging infrastructure
- Academic advisor

Energy Efficiency, Smart contract, data analytics, security



- Funded by Marie Curie and UKRI
- With Africa and EU countries
- To develop smart and traceable agricultural farming using communication, AI and blockchain.

Smart farming, Smart contract, data analytics, security





### Agenda

- Energy transition
  - P2P-3M (EPSRC); NICE (Innovate UK)
- Energy digitalisation
  - Energy-IQ (BEIS)
- Security, risks and uncertainties to energy transition
  - Interlinked computing (NWPST)
- Outlook







### Drivers for energy transition and digitalisation: 3Ds

### **1D** Decarbonisation

Global exercise in reducing carbon footprint drives energy **transition** to sustainable, greener energy systems (Net-zero).

### Decentralisation

2D Centralised generation & transmission results in carbon emissions. Distributed/Multivector energy system drives decentralisation, microgrid and prosumers, which could encourage peer-to-peer energy trading.

### Digitalisation

Emergence of smart meters, **IoT** and **data-driven predictive models** 

enhances energy efficiency and reliability further helping with decarbonisation and

costs savings

**3D** 

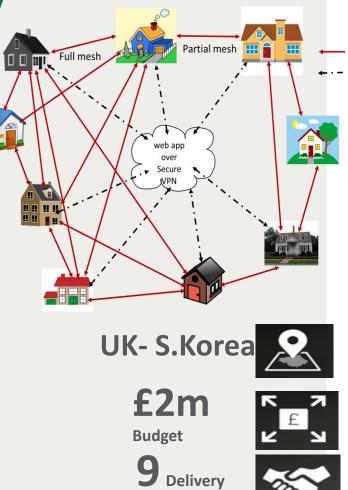


# **Energy transition:** Peer-to-peer energy

trading: How can peer-to-peer energy trading be achieved?

- Prosumer's communication, matching, utility maximisation
- Method: To perform fundamental research on establishing communication between prosumers, matching their resources and maximising their utility while trading energy
- Impact: Environment reduce carbon towards net-zero goal; Economic - cost savings; Society - encourage local energy consumption

Jogunola, O., Adebisi, B., Anoh, K., Ikpehai, A., Hammoudeh, M., & Harris, G. (2022). Multi-Commodity Optimisation of Peer-to-Peer Energy Trading Resources in Smart Grid. Journal of Modern Power Systems and Clean Energy. Jogunola, O., Wang, W., & Adebisi, B. (2020). Prosumers matching and least-cost energy path optimisation for peer-to-peer energy trading. IEEE Access, 8, 95266-95277. Jogunola, O., Adebisi, B., Anoh, K., Ikpehai, A., Hammoudeh, M., Harris, G., & Gacanin, H. (2018). Distributed adaptive primal algorithm for P2P-ETS over unreliable communication links. Energies, 11(9), 2331.



partners



### **Energy Transition - NicE: Nigeria Intelligent Clean Energy Marketplace**

- Aim: To provide access to affordable and clean energy to local communities in Nigeria through the implementation of FPP and P2P-ETS
- Method: To set up a digital twin of the model at MMU for optimisation and scalability
- Impact:
  - Environment reduce carbon towards net-zero goal
  - Economic cost savings
  - Society encourage energy efficiency

Tsado, Y., Jogunola, O., Nawaz, R., Gui, G., & Adebisi, B. (2021). Quantifying Self-consumption and Flexibility Provision through Battery Storage, partners a Deep Reinforcement Learning Approach. ICFNDs. Jogunola, O., Tsado, Y., Nawaz, R., & Adebisi, B. (2021). Energy Trading Strategy, a Deep Reinforcement Learning Approach. EPEC. Tsado, Y., Jogunola, O., Olatunji, F. O., & Adebisi, B. (2022, October). A digital twin integrated cyber-physical systems for community energy trading. *SmartGridComm*. IEEE.



**UK- Nigeria** 

£0.6n

**Budget** 

### NicE: Nigeria Intelligent Clean Energy Marketplace



#### **Capital Science Academy Abuja**



Neighbouring Dafara Community

ναγά

Energy



Cigre For power system expertise

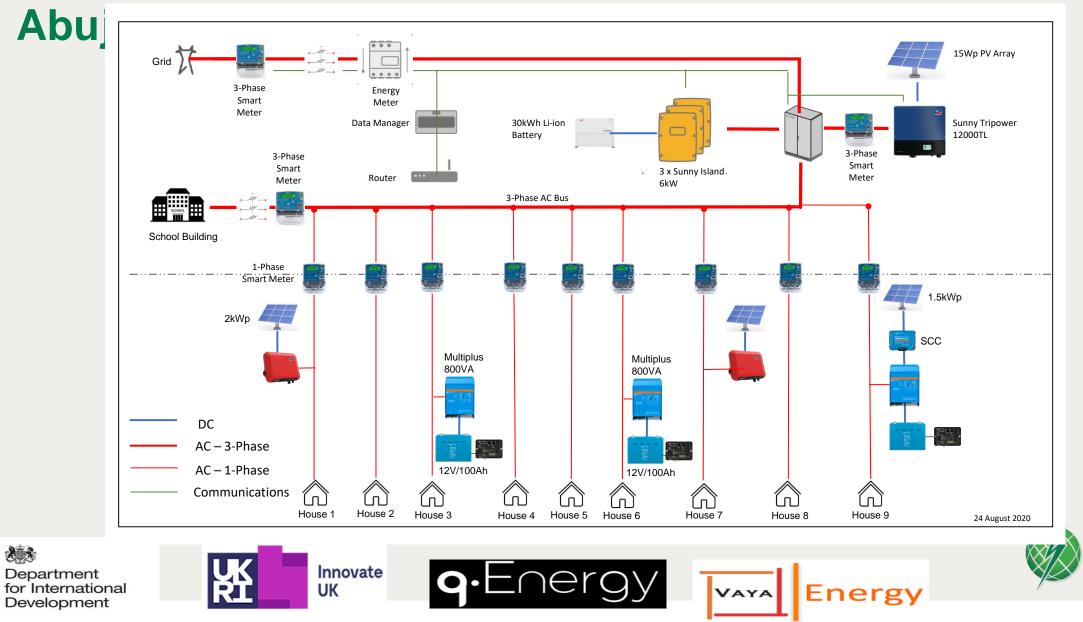
https://guardian.ng/energy/uk-based-energy-solutions-company-provides-nigeriancommunity-with-24-7-renewable-energy/







### NICE pilot architecture at Kuje,



For power system expertis

## **NICE: Community installations**

















partners

VAYA Energy

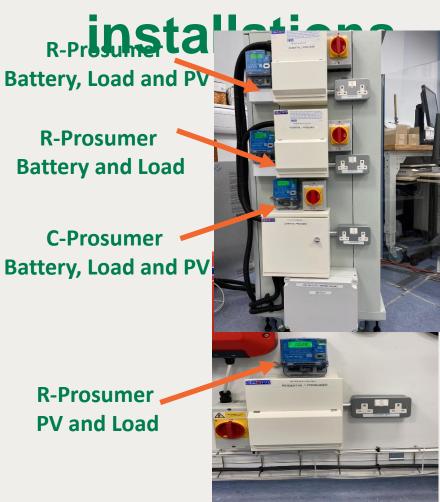
Department for International Development

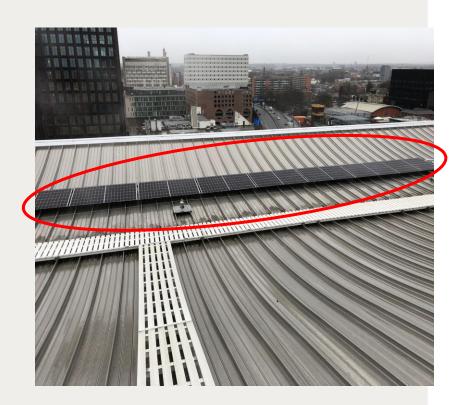




# NICE: MMU lab model &







#### 4 x REC solar 325W solar panels = 1.3kWp array for each prosumer



Department for International Development



**q**•Energ



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enhances energy efficiency and reliability further helping with decarbonisation and

costs savings

**3D** 



**Energy-IQ** savings for SMEs and domestic energy users?

- To trial smart energy services for cost savings
- Method: To investigate AI and smart contract for energy market

**Research on Energy digitalisation:** 

- To develop a predictive analytics framework for demand consumption
- Impact: Environment reduce carbon towards net-zero goal; Economic cost savings; Society – encourage energy efficiency
   £2.2m

Jogunola, O., Adebisi, B., Ikpehai, A., Popoola, S. I., Gui, G., Gacanin, H., & Ci, S. (2020). Consensus Algorithms and Deep Reinforcement Learning in Energy Market: A Review. *IEEE Internet of Things Journal*.
 Tsado, Y., Jogunola, O., Nawaz, R., Gui, G., & Adebisi, B. (2021). Quantifying Self-consumption and Flexibility Provision through Battery Storage, a Deep Reinforcement Learning Approach. ICFNDs.
 Jogunola, O., & Adebisi, B., Hoang, K. V., Tsado, Y. & Popoola, S. I. (2022). CBLSTM-AE: A Hybrid Deep Learning Framework for Predicting Energy Consumption. Energies.
 Jogunola, O., Tsado, Y., Nawaz, R., & Adebisi, B. (2021). Energy Trading Strategy, a Deep Reinforcement Learning Approach. EPEC







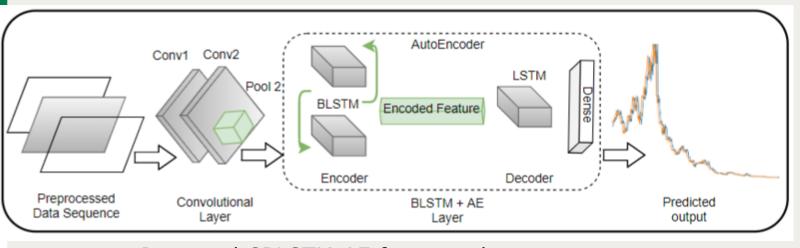
**Budget** 



# **Predictive framework**

Aim: To develop a predictive model for energy consumption prediction

Methodology: Deep learning: LSTM + AE + CNN



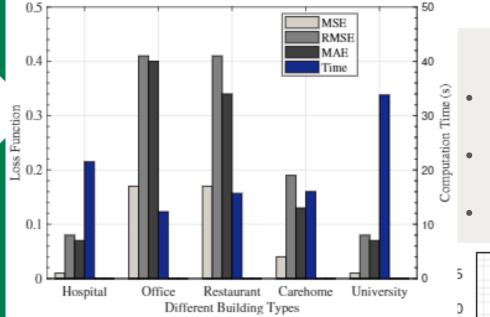
Proposed CBLSTM-AE framework

Result: Performance improvement in computation time of 56% and mean squared error of 80% to benchmark

**Jogunola, O.,** & Adebisi, B., Hoang, K. V., Tsado, Y. & Popoola, S. I. (2022). CBLSTM-AE: A Hybrid Deep Learning Framework for Predicting Energy Consumption. Energies.

Algorithm 1: CBLSTM-AE Algorithm 1 Input X 2 Output d 3 Initialise  $\omega$ 4 for  $i = l \in n$  do for  $j = l \in m$  do 5 calculate  $P_i$  from (4)  $i_t = \sigma \overleftarrow{(W_{pi}Pt} + \overleftarrow{W_{hi}h_{t-1}} + W_{ci} \cdot c_{t-1} + \overrightarrow{b_i}$  $f_t = \sigma \overrightarrow{(W_{pf}Pt} + \overrightarrow{W_{hf}h_{t-1}} + W_{cf} \cdot c_{t-1} + \overrightarrow{b_f}$ 7  $o_t = \sigma(\overline{W_{po}Pt} + \overline{W_{ho}h_{t-1}} + W_{co} \cdot c_{t-1} + \overline{b_o})$ 8  $c_t = f_t \cdot c_{t-1} + i_t \cdot \sigma (W_{pc}p_t + W_{hc}h_{t-1} + b_c)$  $h_1 = o_1 \cdot \sigma(c_1)$ 10 end 11  $\bar{y} = \sigma(W_y h_1' + b_y)$ 12 for  $j = l \in m$  do 13  $i_t = \sigma(W_{vi}\bar{y}t + W_{hi}h_{t-1} + W_{ci} \cdot c_{t-1} + b_i)$ 14  $f_t = \sigma(W_{uf}\bar{y}t + W_{hf}h_{t-1} + W_{cf}\cdot c_{t-1} + b_f)$ 15  $o_t = \sigma(W_{po}\bar{y}t + W_{ho}h_{t-1} + W_{co} \cdot c_{t-1} + b_o)$ 16  $c_t = f_t \cdot c_{t-1} + i_t \cdot \sigma(W_{pc}p_t + W_{hc}h_{t-1} + b_c)$ 17  $h_1 = o_1 \cdot \sigma(c_1)$ 18 19 end  $\hat{y} = \sigma(W_y h_t + b_y)$ 20 $\vec{d}_i^k = \sum_j w_{ji}^k - 1(\sigma(\hat{y}_i^{k-1}) + b_i^{k-1})$ 21 22 end **23**  $d = \{\overline{d}\}$ 





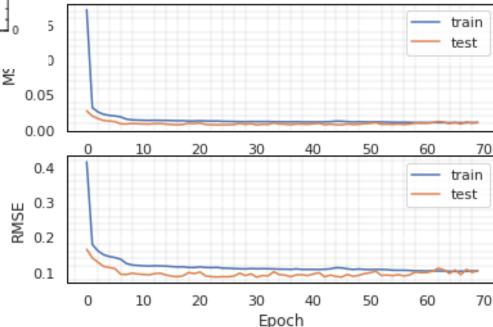
### **Different Energy dataset**

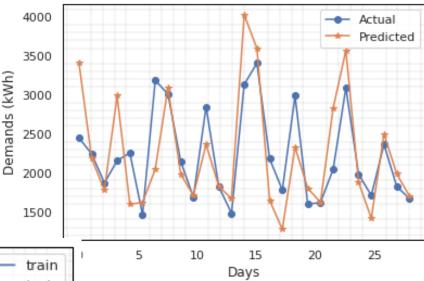
Increase in length of data result in

- Increase in computation
  time
- Decrease in measured loss

## **Results**

- To show the skilfulness of the proposed solution
- Training and validation loss for MSE and RMSE
- MSE of 0.01, RMSE of 0.09





#### **Actual and predicted**

- To illustrate the predictive fit with actual data
- A months' prediction showing good fit

### **Training and validation loss**

**Jogunola, O.,** & Adebisi, B., Hoang, K. V., Tsado, Y. & Popoola, S. I. (2021). CBLSTM-AE: A Hybrid Deep Learning Framework for Predicting Energy Consumption. IEEE Internet of Things (under review).

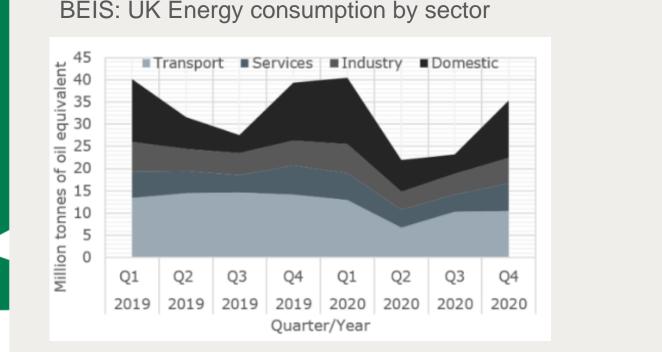


# **Post-Covid energy consumption**

Ain Transfer and its impact on smart energy service landscapes

Methodology: Review and predictive analysis

Sample energy data for 5 commercial buildings

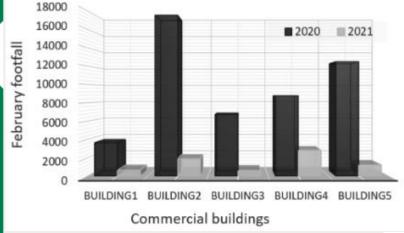


Building1 500000 demand (kWh) Building2 Building3 400000 Building4 Building5 300000 Monthly 100000 100000 Feb 19 Jun 19 Jun 19 Aug 19 Oct 19 Dec 19 Jun 20 Apr 20 Aug 20 Oct 20 Oct 20 Dec 20 Jun 18 Aug 18 Oct 18 Dec 18 Apr 18

Result: To inform policy on energy and intervention towards net-zero carbon, costs savings

**Jogunola, O.,** Morley, C., Akpan, I. J., Tsado, Y., Adebisi, B., & Yao, L. (2022). Energy consumption in commercial buildings in a post-covid-19 world. *IEEE Engineering Management Review*, *50*(1), 54-64.

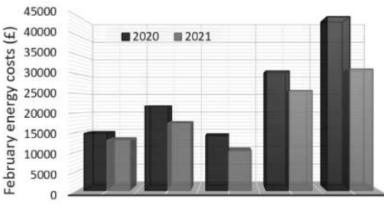
# Results



# February occupancy: Average of 10% of 2020 footfall

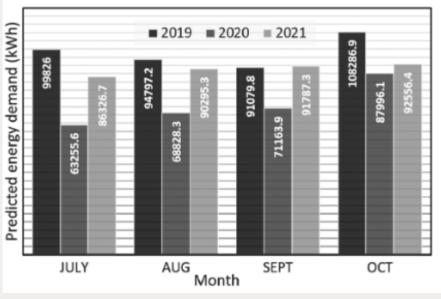


- 29%, 38%, 45%, 37% higher than covid
- 8%, 19%, 39%, 1% higher than precovid



BUILDING1 BUILDING2 BUILDING3 BUILDING4 BUILDING5 Commercial buildings

# February costs: Average of 80% of 2020 costs

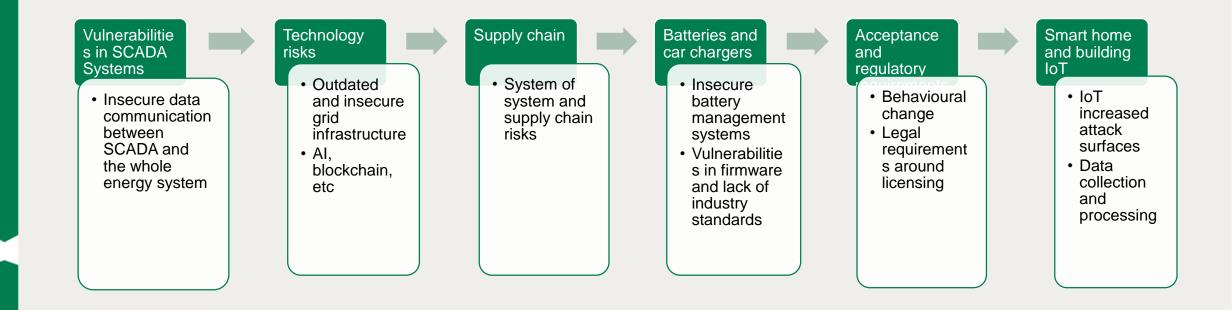


4-month energy prediction for building 1

Jogunola, O., Morley, C., Akpan, I. J., Tsado, Y., Adebisi, B., & Yao, L. (2022). Energy consumption in commercial buildings in a post-covid-19 world. *IEEE Engineering Management Review*, *50*(1), 54-64.



### Security, risks and uncertainties to Energy Transition



RUSI (2022), Securing a Net-zero Future. Available <u>https://static.rusi.org/305-EI-Cyber-Risks.pdf</u> Yuan, H., & Li, S. (2022, June). Cyber Security Risks of Net Zero Technologies. In *2022 IEEE Conference on Dependable and Secure Computing (DSC)* (pp. 1-11). IEEE. **Jogunola, O.,** Ajagun, A. S., Tushar, W., Olatunji, F. O., Yuen, C., Morley, C., ... & Shongwe, T. (2024). Peer-to-Peer Local Energy Market: Opportunities, Barriers, Security and Implementation Options. *IEEE Access*.



#### Cyber Security Threats to Energy Transition

#### IOT SECURITY

#### Hackers Earn \$1.3M for Tesla, EV Charger, Infotainment Exploits at Pwn2Own Automotive

Participants have earned more than \$1.3 million for hacking Teslas, EV chargers and infotainment systems at Pwn2Own Automotive.



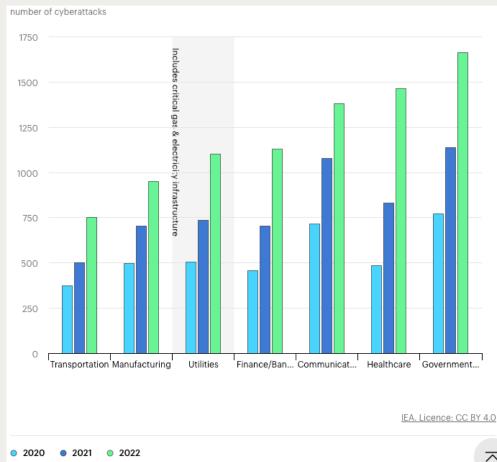
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A / News / "Top Python Developers Hacked In Sophisticated Supply Chain Attack"

### "Top Python Developers Hacked in Sophisticated Supply Chain Attack"

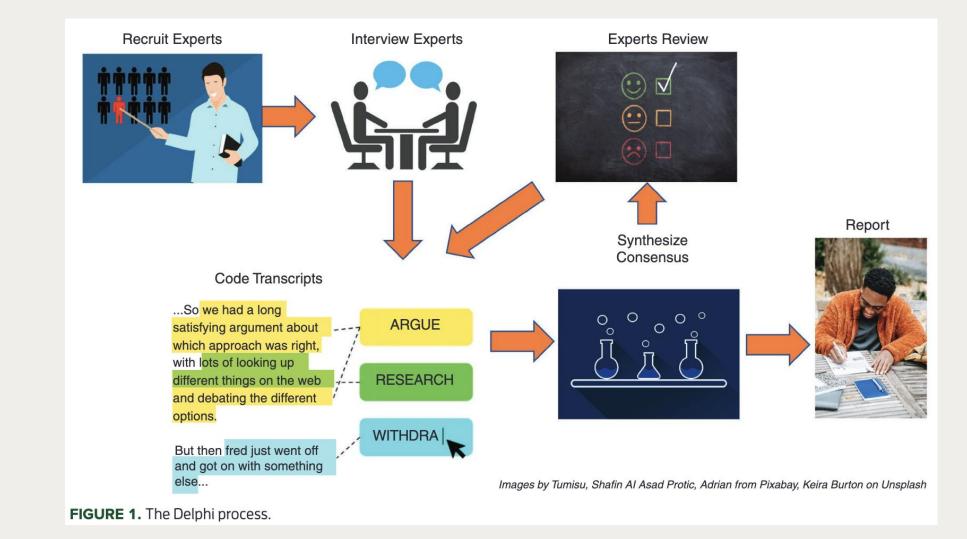
Checkmarx reports that multiple Python developers, including a Top.gg maintainer, were infected with information-stealing malware after downloading a malicious clone of a popular tool. Colorama, a tool that makes ANSI escape character sequences work on Windows, has over 150 million monthly downloads. The

### The average number of weekly cyberattacks per organisation in selected industries





#### Cyber Security – Interlinked Computing: System of System Security





C. Weir, A. Dyson, **O. Jogunola**, L. Dennis and K. Paxton-Fear, "Interlinked Computing in 2040: Safety, Truth, Ownership, and Accountability," in Computer, vol. 57, no. 1, pp. 59-68, Jan. 2024, doi: 10.1109/MC.2023.3318377.

### Future outlook – Interlinked computing

TABLE 2. Agreement with statements.													
	Forecast	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14
F1	Cutting corners in safe AI												
	leading to a megadeath incident												
	due to regulatory capture												
	which has developed exponentially												
F2	Quantum processing only just being used												
F3	Difficulty distinguishing truth from fiction												
F3	Tokenization for ownership of web assets												
F5	Cannot distinguish accidents from incidents												
	systems beyond human understanding												
	with more accidents due to complexity												

Blue: agree; white: no opinion or unsure; amber: disagree.



C. Weir, A. Dyson, **O. Jogunola**, L. Dennis and K. Paxton-Fear, "Interlinked Computing in 2040: Safety, Truth, Ownership, and Accountability," in Computer, vol. 57, no. 1, pp. 59-68, Jan. 2024, doi: 10.1109/MC.2023.3318377.

# Thank You!

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