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An integrated Augmented Reality (AR) and embedded electronics-based toolkit for improved visualization and understanding of network graphs

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Abstract

Network graphs are all-pervasive, and an in-depth understanding of networks is important for students and researchers across a variety of disciplines that involve analysis of multi-modal data. Networks can be challenging to conceptualize due to their complexity, and immersive technologies are needed to parse network graphs. This study introduces a novel immersive toolkit grounded in multimedia learning and embodied cognition theories to improve network graph comprehension in undergraduate STEM students. The toolkit integrates embedded electronics with Augmented Reality (AR) to create synchronized physical-virtual visualizations of complex networks featuring: (1) visual attributes to communicate network properties, (2) tactile interaction through physical network models, (3) local and global views of network graphs, and (4) contextual AR overlays. We present two implementations of this toolkit, one of which was implemented as a case study (intervention) in a senior-level undergraduate class (N = 25) during finals week with statistically significant improvement (FDR adjusted p = 0.0018) in study outcomes post-intervention compared to pre-intervention. Notably, the improvement was pronounced among students that reported low confidence in subject matter pre-intervention. This study demonstrates how technology can be used to augment human cognition for complex mental tasks and demonstrates the utility of our toolkit to serve as a technology-enabled teaching aid.

1. Introduction

In an increasingly complex and rapidly changing world, educational systems must adapt to prepare students for future success in academia, Government, and industry. In the 21st century, there has been a surge towards adopting computational thinking into modern curricula. Computational thinking is defined as “solving problems, designing systems, and understanding human behavior, by drawing on the concepts fundamental to computer science” [1], Computational thinking has been recognized as the foundation for all science, technology, engineering, and mathematics (STEM) disciplines, not just due to the growing use of computer science (CS) in non-CS disciplines, but because of its ability to solve complex problems in non-CS disciplines through the use of abstraction and algorithms [2]. The large interconnected systems encountered in these complex problems are often represented as network graphs, and as such, it is critical to develop network graph analysis skills for STEM students exiting institutions of higher education.

1.1 Utility of network graphs in education

Networks are collections of interconnected entities widely used in academia, Government, and industry to understand the dynamics of the system under consideration, e.g. utilizing layers of online data for personalized marketing campaigns [3], utilizing transportation data for traffic control [4], utilizing customer purchasing patterns for fraudulent banking activity detection [5], etc. Network graphs represent data in the form of “nodes” (the entities) and “edges” (the relationships between entities). Both nodes and edges can be assigned different properties or attributes. For example, nodes could correspond to a single layer of data (e.g., social media “friends” network) or could correspond to multiple layers that are independently or hierarchically linked to each other. Network graph analysis is commonplace in public health/biology research, e.g., to understand interactions between proteins in a biological pathway [6], spread of a pandemic over space and time using claims data [7], inter-relationships among diseases from electronic health records [8], and so forth. Due to the wide range of real-world applications for network graph analysis, researchers are exploring practical examples to adopt in STEM curriculums [9, 10]. However, the educational value of network graphs depends not only on their analytical capabilities, but also on how effectively learners can interpret and engage with them.

While active learning is effective across sample sizes for STEM in general [11], visual aesthetics have been shown to have strong impacts on the utility, affordance, and readability of network graphs [12]. The “Connections: The Nature of Networks” museum exhibition developed by the New York Hall of Science found the most popular and effective aspects were when visitors physically interacted with networks [13]. Thus, effective educational use of network graphs requires careful attention to visual design and opportunities for interaction.

1.2 Current methods and challenges in network graph visualization

State-of-the-art network graph visualization incorporates advanced techniques in data visualization, machine learning, and distributed computing. These involve graph databases such as Neo4j [14] and ArangoDB [15] for creating “knowledge graphs”; scalable tools such as Gephi [16], Cytoscape [17], and Graphistry [18] that use efficient algorithms to filter and cluster networks (such as node and edge filtering, clustering or community detection); and web-based visualization frameworks based on JavaScript libraries such as D3.js [19], Sigma.js [20], and KeyLines [21] that create interactive graph visualizations. Many of these tools use a force-directed graph approach to increase the fidelity of the network. Advanced deep learning tools such as Graphical Neural Networks [22] also learn from graph-structured data while dimensionality reduction techniques such as t-SNE [23] and UMAP [24] help with data visualization in a lower dimensional space. Interactive dashboards and platforms such as Tableau and Power BI [25] enable interactive visualizations by integrating several big data sources together. Specialized tools like Tulip [26] and Pajek [27] can accommodate specific cases like visualization of relational data or extension to millions of network nodes.

Most of the research on network readability and understanding focuses on the two-dimensional representation of network structure, relying on graph sampling, filtering, partitioning, clustering, or combinations thereof [28]. This approach works well for simple topologies; however, as the number of connections increases in a network with many nodes, it becomes less interpretable. The resulting structure often resembles a “hairball,” especially when using 2D network graph visualization tools like Gephi and Cytoscape. These networks become difficult to parse, limiting our ability to fully communicate the interpretation and utility of the network. In addition, practical data is often multi-layered and difficult to effectively visualize using the above-mentioned tools due to the limited number of visual attributes in two dimensions. These tools also cannot accommodate scenarios where one is interested in understanding the direction or strength of relationships between network nodes. As such, some of the more interactive tools attempt to resolve these issues by allowing graph selections and structural/topological navigation to only display a local area of interest.

However, a key challenge in adopting these interactive visualization tools within an educational setting is that each method typically has its own unique querying language [29]. This causes large learning curves for students, making it difficult for those not going into computer science or applied mathematics to reap the benefits of learning network graph analysis. Additionally, many of the interactive visualization tools (e.g., Tulip, Pajek, Keylines, Tableau, PowerBI) are not open source, meaning they cannot be freely downloaded and accessed either by educators or students.

1.3 Use of tactile/immersive technology to improve student learning

A growing body of research points to the utility of adopting tactile and interactive environments facilitated via 3D printing to improve learning outcomes in undergraduate STEM education with hands-on experiential learning, enhanced engagement, and improved understanding and creativity [30]. Extended reality (XR), which encompasses Virtual (VR), Augmented (AR) and Mixed (MR) Reality, is also increasingly being accommodated in undergraduate classrooms across a multitude of fields to improve engagement levels [31–33]. VR traditionally refers to users being fully immersed in digital worlds via head-mounted displays, AR traditionally refers to users viewing a digital overlay overtop of the physical world through a hand-held device, such as a smart phone, and MR traditionally refers to users viewing both the physical and digital world with interactive digital overlays displayed through head-mounted display systems. These innovative tools are revolutionizing educational landscapes, particularly within STEM fields for undergraduate students. They offer dynamic and interactive learning experiences through captivating visuals and contextual information that traditional methods cannot match, fostering deeper engagement and understanding of complex scientific concepts. For example, emerging research in Human Computer Interaction found that VR educational interventions improved learning gains for chemistry students when learning about fluid flow dynamics [34]. The study also found that students reported higher levels of engagement and enjoyment in the VR condition as compared to a more traditional educational experience. These findings align with prior work that suggest immersive technologies can significantly increase student engagement with course content [35]. Within STEM, prior work has explored the utility of immersive technologies to teach students hands-on lab

skills or simulate complex physical tasks while removing safety or financial concerns [35]. Immersive technologies have also been extensively explored within medical training as a viable option to allow students and residents to engage with virtual patients and simulate surgery, for example, at zero risk to actual human patients [36]. In many of the reviewed studies, immersive technologies offer a novel modality for engagement with traditional concepts; in other words, learners tend to engage more readily with immersive technologies because the technology itself is “new” or “exciting” to them, offering them a novel pathway to engage with material. However, VR exists purely in a virtual environment, making interactions with physical objects difficult. Additionally, MR systems demand more cognitive load from users which can lead to increased anxiety, frustration, and decreased performance [37]. As such, AR was selected as the most suitable of the immersive technologies for the toolkit.

1.4 Integrated toolkit to visualize network graphs

We have developed an integrated toolkit that enables (1) Effective understanding of the interconnectivity between network nodes using multi-layered data, and (2) Powerful demonstration of complex networks in a classroom setting, serving as a technology-enabled teaching aid for undergraduate faculty. It is akin to the “Marshmallow Challenge” in which we build network structures out of 3D printed nodes with embedded electronics in place of marshmallows and LED strip lights in place of the spaghetti sticks. Our approach is highly dynamic, featuring moving flows of LEDs along edges, changes in LED colors, selective activation of sub-networks, etc. Our toolkit can create a physical network display in a cost-effective manner using LED lighting and QR codes at each network node. In addition, it uses a single Microsoft HoloLens 2 headset to display the Augmented Reality (AR) virtual overlay (reading each QR code as a virtual object), with a remote control-like web interface to select the nodes to be visualized in the HoloLens.

Critically, this tool is grounded in theories of multimedia learning, cognitive load theory, and embodied cognition. Multimedia learning theory posits that learners process information through partially independent visual and verbal channels, and that learning is enhanced when representations are coherently integrated rather than fragmented [38, 39]. Cognitive load theory further suggests that instructional designs that reduce extraneous processing while preserving germane load can facilitate schema construction and relational reasoning [40]. Embodied cognition extends this framework by arguing that abstract reasoning is grounded in perceptual and motor systems, such that physical interaction can scaffold conceptual understanding [41].

The design rationale of our toolkit follows directly from these principles. Traditional 2D network graphs often compress multi-layered relationships into dense visual fields that require high intrinsic cognitive load to parse. By externalizing topology into a stable physical structure (3D printed nodes and programmable edges) while layering dynamic transformations through MR overlays, the system distributes processing across spatial, visual, and interactive channels. This reduces representational ambiguity for the learner, anchors abstract transformations to physical reference points, and allows learners to manipulate parameters without reconstructing the underlying structure.

In summary, current methods of network graph visualizations present large learning curves to students due to unique querying languages and lack of open-source softwares. Additionally, as networks get more complex and dense, 2D-visualization results in edge crossings that clutter the graph. In this paper, the authors developed a novel toolkit that harnesses the capabilities of immersive technologies to display a synchronized physical-virtual visualization of network graphs. We present two different prototypes utilizing our toolkit for visualization of networks – one of which was tested as a case study in an undergraduate STEM course and led to substantial gains in learning outcomes. This versatile tool includes several key attributes: (1) Additional attributes via dynamic LED and AR displays to visualize multi-dimensional data, (2) Tactile interactivity via physical network models, (3) Local and global views of network graph, and (4) Contextual information via AR overlay.

2. Methods

The toolkit consists of a physical network display interfaced with a virtual AR overlay. The physical model contains all relevant nodes and edges in the network, with microcontrollers and LEDs embedded inside to control network behavior. The virtual model exhibits engaging visuals and contextual information to allow users to inference relationships within the network. To assess the toolkit's viability as an educational tool, research was conducted in two prototypes. The first, lower fidelity prototype featured atypical methods of displaying relational data between network nodes due to physical limitations imposed by translating a digital model into reality. This prototype was piloted within a small group of scientists and experts to gather qualitative feedback on the effectiveness and intuitiveness of its presentation. The second, higher fidelity prototype was tailored for an upper-level statistics class to collect quantitative and qualitative data on overall engagement, enjoyment, and knowledge retention of undergraduate students when using the toolkit.

2.1 Prototype 1: A genetic network

The first prototype aimed to determine how multilayered networks could be visualized in physical space. To do so, we constructed a sample proof-of-concept network focused on biological/disease data from a separate analysis (manuscript in progress) focused on large-scale biomedical database called the UK Biobank [42, 43] and the Genotype Tissue Expression Consortium (GTEx) v8 [44]. In this separate analysis, our goal was to understand the genetic overlaps between brain image derived phenotypes or IDPs (based on structural and diffusion MRI) and diseases from electronic health records across multiple organ systems (e.g. diseases of the circulatory system, nervous system, immune system, respiratory system, etc.) to disentangle the shared and distinct biological mechanisms linking genetic risk, systemic disease, and structural brain changes. We first conducted genome-wide association study (GWAS) on ~ 2000 brain image-derived phenotypes in the UK Biobank using the tool Regenie [45]. Subsequently we identified the number of GWAS-significant genetic markers that were also associated with gene expression across 49 different tissues in the GTEx cohort. Finally, we looked at the subset of genetic associations (with functional relevance) that were associated with International Classification of Disease (ICD) codes across multiple organ systems in the UK Biobank using a IDP-guided phenome-wide association study [46]. Given the complexity of our results, we decided to visualize them via an interactive knowledge graph in Neo4j [47] (manuscript in progress). For this paper, we selected a small subset of this larger network that would be ideal for visualization within a classroom setting. Our network shows associations between 4 layers of data: (a) DNA single nucleotide polymorphism markers, (b) 12 brain MRI phenotypes pertaining to volumes of gray matter (*N*=38K), (c) coronary atherosclerosis cases/controls obtained from electronic health records data (*N*=452K), and (d) and gene expression of the two genes *FURIN* in esophagus mucosa (*N* = 497) and *WDR12* in nucleus accumbens - basal ganglia in the brain (*N* = 202), both of which are genes known to play a role in cardiovascular disease. The data was first visualized within Gephi [48]. The Yifan Hu layout algorithm was applied before each node was labeled and color coded to its respective layer (Fig. 1).

At a minimum, the toolkit needed to meet the level of visualization accomplished using Gephi. It needed to distinguish between layers of nodes, exhibit directions and strengths of association between nodes, and display node labels. In addition, we were interested in a dynamic network visualization that showcased the ability to explore local and global views of the network as well as included engaging visuals to provide context to users unfamiliar with the biological terms. To minimize the learning curve of using the toolkit, we opted to use colors to distinguish node layers and directions of effects to maintain consistency with the Gephi visualization.

2.1.1 Development of the genetic network virtual model

A Unity [49] app was developed to create a virtual environment using the OpenXR [50] plugin. The 3D models of brains, tissue, and genes were created in Autodesk Maya, with highlighted focus regions set up using Adobe Photoshop. These visuals, alongside the node labels, are generated once their respective QR codes were scanned within the app. To display the AR virtual overlay, a user wears a HoloLens 2 headset and launches the Unity app, which turns the camera on and automatically scans any QR codes within its field of view.

2.1.2 Construction of the genetic network physical model

Network nodes were designed as polyhedral shells to house the embedded electronics. Depending on the degree (number of connections) of the node, cubes or dodecahedron were used. To allow ease of assembly, each face featured press-fit male and female joints with a rectangular slot in the middle of the face through which network edges could be attached. The faces were 3D printed out of transparent polylactic acid (PLA) due to their irregular geometry, low cost, and easy viewing of internal LEDs.

Network edges were constructed with strips of ten WS2812B LEDs inside clear polyvinyl chloride (PVC) tubing for protection. Each LED could be individually addressed, allowing full control over the color, brightness, and pattern of the lights. These properties were used to demonstrate network characteristics.

The ESP32-WROOM-32 Development Board [51] was used to drive the physical model behavior. Its small size (3.78 x 2.36 x 0.71 inches) fits inside of the 3D printed node shells but still features 25 General-Purpose Input/Output pins for writing data to the node and edge LEDs. Additionally, its 2.4 GHz Wi-Fi enabled communication between several ESP32s as well as synchronization between the physical and virtual model. The Arduino IDE [52] was utilized due to its compatibility with the ESP32 and open-source libraries such as FastLED [53] for controlling addressable LEDs and ESP-NOW [54] for wireless communication. Open-source projects from Random Nerd Tutorials [55] were also referenced for establishing the ESP32 boards as Wi-Fi stations and sending/receiving messages.

2.1.3 Genetic network demonstration

We developed 6 scenarios to guide new users through interpreting the genetic network and our toolkit. In the physical model, only the nodes being visualized in the scenario are lit up. Scenario 0 begins as a baseline model of a single *FURIN* gene as a central node. Scenario 1 introduces the first expression quantitative trait locus (eQTL) mapping to *FURIN* in the esophagus mucosa tissue and its associations with IDPs. In this scenario, users can note the opposing flows of light and colors to distinguish between positive and negative associations. They can also note the colored LEDs embedded in the physical nodes to distinguish between different node layers. Scenario 2 expands the network view and adds more eQTLs mapping to the *FURIN* gene and the IDPs associated with them. With the greater number of edges, the user can differentiate between hues and relate them to the strength of association. Scenario 3 introduces the final layer of node – cardiovascular disease. Scenario 4 displays the full “global” view of the network by adding in the other central node (*WDR12* gene) and all its connected nodes (Fig. 2). Finally, scenario 5 allows the user to explore a local view of the last added *WDR12* node, its eQTL in the nucleus accumbens tissue, and its association with IDPs.

Users were able to toggle between the various scenarios via a remote control-like web interface that featured buttons for each of the 6 scenarios. The HoloLens 2 was connected to WiFi, where it could read the current scenario and adjust the virtual model accordingly. However, a limitation of Prototype 1 was the lack of communication between virtual and physical models. An extra user input was required using a physical button station to adjust the LED lights to the current scenario. Additionally, Prototype 1 was presented as a live demonstration at the American Society for Human Genetics 2023 conference to researchers working in the fields of public health and epidemiology, statistical, computational, and population genetics, bioinformatics, and molecular biology. Although it received excellent feedback, conclusions on its effectiveness as a learning tool could not be drawn from users already experienced in the subject matter. Instead, the genetic model was presented as a proof-of-concept prototype that could communicate critical network characteristics. A detailed demonstration of the genetic model is available in the supplementary material (Video S1).

2.2 Prototype 2: Probability distribution network

The second prototype focused on relationships between different probability distributions – univariate discrete vs univariate continuous – and was used as a case study in a senior level statistics course. The case study was conducted over the Spring 2024 semester on a population of $N = 25$ students (STAT 414 – Introduction to Probability Theory) at

Pennsylvania State University. This course focuses on understanding the fundamental properties of probability, discrete random variables and probability distributions, continuous random variables, and probability distributions (both univariate and bivariate) and large sample theory. The objective was to study the utility of our toolkit in understanding a network of probability distributions. We had six univariate discrete distributions (Poisson, binomial, geometric, negative binomial, hypergeometric) and six univariate continuous distributions (Gaussian, gamma, beta, chi-squared, exponential, uniform). There were 6 cases focused on how one distribution transforms to another, i.e., upon (i) taking the limit on a parameter, (ii) applying variable transformations, (iii) conditioning on a random variable, (iv) convolution, i.e., sum of independent and identically distributed random variables, (v) applying the central limit theorem, (vi) setting a parameter to a fixed value. We focused on 28 "pairs" of distributions (parent: target) across all six cases – each pair being referred to as a scenario. Each scenario was represented as an edge in the network graph, with the probability distributions comprising the nodes (Fig. 3). The full list of scenarios and their respective cases and transformations is available in the supplementary material (Table S1).

2.2.1 Development of the probability distribution network virtual model

A similar Unity app was developed for the Probability Distribution Network virtual model. When scanning the node QR codes, labels containing the names of the probability distributions are generated. Additionally, a website featuring graphs of the source and target distributions is projected above the network for the user to see how they converge as parameters are adjusted in real-time. To allow the user to control the parameters via a laptop or phone, a remote control-like web interface was developed with simple inputs (i.e., buttons, sliders, etc.). Selection menus were created so that users could sequentially select the case, scenario, and parameters they wanted to see. Figure 4a depicts the case selection menu, Fig. 4b depicts the scenario selection menu for Case 5: Central Limit Theorem (CLT), and Fig. 4c depicts the parameter selection menu for the geometric to Gaussian scenario. The remote for the case, scenario, and parameter selections is available at cie.psu.edu/networkMR/distributions/remote.html.

The corresponding graphs are displayed in Fig. 5. The red distribution is the geometric distribution (the source), with probability of success p which remains constant. The blue distribution is the average of n samples sampled from the geometric distribution (the transformation). The black graph is the Gaussian distribution (the target) with the following parameters: $\mu = \frac{1-p}{p}$ and $\sigma^2 = \frac{1-p}{n*p}$. Figure 5a shows the graphs for n = 5, Fig. 5b shows them for n = 10, and Fig. 5c shows them for n = 100. The CLT states that the average of many samples of any distribution will converge to a Gaussian distribution, which is why the blue and black graphs match more closely as the sample size increases. The viewer for the graphs is available at https://cie.psu.edu/networkMR/distributions/viewer.html. Additional examples of cases and scenarios are available in supplementary material (Figures S1-S4).

2.2.2 Construction of the probability distribution network physical model

The probability distribution network was constructed in a similar manner to the genetic network, with the same embedded electronics inside transparent 3D printed shells. However, further integration between physical and virtual models was achieved using PHP websites as a proxy server. The embedded ESP32 microcontrollers send HTTP GET requests to the PHP site through their WiFi connection. The PHP site updates which scenario, and its respective nodes, are currently selected by the user via a binary list. This information is then relayed to the embedded microcontrollers, which updates the physical display of LED lights. This feature allows real-time switching between scenarios with no input required from the instructor, creating greater autonomy in user exploration.

2.2.3 Probability distribution network demonstration

The full physical-virtual probability distribution network model (depicted in Fig. 6) was demonstrated to the class in the final week of STAT 414. Due to the availability of a single HoloLens 2 headset, the instructor's point-of-view was streamed to the entire class via Microsoft Teams and Dynamics 365 Remote Assist. After a walk-through of the network graph, students were invited to interact with the physical-virtual model individually. A detailed demonstration of the probability distribution model is available in the supplementary material (Video S2).

We administered knowledge-based questionnaires to students before and after the demonstration. These questionnaires comprised 18 multiple choice questions pertaining to the material covered in STAT 414 over Spring 2024 (Table 1) for which students needed to select one correct answer. E.g., for Q15 "*Can we go from Binomial distribution to Normal distribution?*", these were the choices: (A) No; (B) Yes, as the sample size goes to infinity; (C) Yes, as the probability of success goes to 0; (D) Yes, as the probability of success goes to 0.5; (E) Yes, by applying Central Limit Theorem, sample mean converges to normal as sample size approaches infinity; (F) B, D, E; (G) B,E. The correct answer was (F). For a full list of questions along with the multiple-choice options, please refer to Table S2. In addition, there were subjective multiple-choice questions (e.g., What is your confidence level in the course, on a scale of 1–5, how engaging was the experience) as well as qualitative questions (e.g., describe your experience with the demonstration). We satisfied the assumptions of normality of our pre- and post-intervention response variables using a Shapiro-Wilk test. We applied paired samples t-test to compare group means before and after the intervention (i) in the entire class (ii) among those that reported "low" confidence levels in the subject matter pre-intervention and (iii) among those that reported "moderate" confidence levels in the subject matter pre-intervention (i) among those that thought their confidence levels improved after intervention, (v) among those that thought the intervention was useful, (vi) among those that thought the intervention improved their understanding, (vii) among those that thought the intervention was engaging, and (vii) among those that wore the HoloLens 2 subsequent to following the demonstration given by the instructor. Internal consistency reliability of the binary-scored assessment was evaluated using Cronbach's alpha.

Table 1
Knowledge-based multiple-choice questions asked to students in the case study.

Question number	Knowledge-based multiple-choice question asked
Q1	Can we go from Gamma distribution to Exponential distribution?
Q2	Can we go from Geometric distribution to Normal distribution?
Q3	Can we go from Uniform distribution to Normal distribution?
Q4	Can we go from Negative Binomial distribution to Geometric distribution?
Q5	Can we go from Hypergeometric distribution to Bernoulli distribution?
Q6	Can we go from Poisson distribution to Binomial distribution?
Q7	Can we go from Hypergeometric distribution to Binomial distribution?
Q8	Can we go from Uniform distribution to Exponential distribution?
Q9	Can we go from Binomial distribution to Hypergeometric distribution?
Q10	Can we go from Uniform distribution to Beta distribution?
Q11	Can we go from Geometric distribution to Negative binomial?
Q12	Can we go from Binomial distribution to Poisson distribution?
Q13	Can we go from Exponential distribution to Chi-squared distribution?
Q14	Can we go from Exponential distribution to Gamma distribution?
Q15	Can we go from Binomial distribution to Normal distribution?
Q16	Can we go from Negative Binomial distribution to Gamma distribution?
Q17	Can we go from Poisson distribution to Normal distribution?
Q18	Can we go from Normal distribution to Chi-squared distribution?

All methods were carried out in accordance with relevant guidelines and regulations. All experimental protocols for the case study were submitted for Institutional Review Board (IRB) review via Penn State's Centralized Application Tracking System for IRB (STUDY00024234 "3D-4-BigData: 3D Printed Electronics enabled 4D Visualization of Large Network Graphs"). The Human Research Protection Program at Penn State determined that the study does not require formal IRB review because the research met the criteria for exempt research according to the policies of this institution and the provisions of applicable federal regulations. Informed consent was obtained from all students who participated in the study and a unique study ID was created for each student to keep their names anonymous. The pre- and post-intervention questionnaires were administered to the class via the Qualtrics Survey tool licensed by Penn State.

3. Results

Twenty-five individuals answered the survey. All individuals were in the 18–25 age range, except one who was 29 years old. Three were first-year students, 17 were juniors, four were seniors, and one was a PhD student. Three were Actuarial science majors, 11 were Data science majors, two were Engineering majors, two were Mathematics majors, two were Physics majors, two were Statistics majors, and two reported "Other" majors. One was a PhD student in biological sciences. Twenty-one males and four females answered the survey (see Tables S3-S10). Twenty-one out of 25 students either agreed or strongly agreed that the demonstration was engaging. Sixteen out of 25 students either agreed or strongly agreed that their confidence level in the material improved after the presentation. We used false discovery rate (FDR) for adjustment of multiple comparisons.

We found a highly significant improvement in student scores for the 18 objective questions post-intervention compared to pre-intervention (N = 25, FDR adjusted p-value = 0.0018, confidence interval = [1.60, 4.47]) by applying the paired t-test. *Importantly, the smaller cohort with low confidence in subject matter pre-intervention (N = 14) also showed significant improvement in test scores (FDR adjusted p-value = 0.012, confidence interval = [0.80, 5.19])* (Fig. 7). Additional paired t-tests were conducted on subpopulations, with those yielding significant results shown below in Table 2.

Table 2
Statistically significant improvements in knowledge-based questions using paired t-tests within selected subpopulations of students surveyed.

Subpopulation	Sample Size (*N*)	FDR adjusted p-value	Confidence Interval
Moderate confidence in subject matter pre-intervention	10	0.017	[0.7, 5.49]
Agreed or strongly agreed that their confidence level improved after the intervention	16	0.012	[0.80, 4.57]
Agreed or strongly agreed that the intervention was a useful exercise	19	0.003	[1.47, 4.84]
Agreed or strongly agreed that the intervention was engaging	21	0.002	[1.49, 4.60]
Did not wear the HoloLens but followed along with the instructor's presentation	14	0.012	[0.76, 3.95]
Wore the HoloLens after the instructor's presentation	11	0.013	[1.09, 6.72]

Our toolkit demonstrated acceptable reliability for exploratory educational research (α = 0.78). Three items showed negative correlations with the dominant item structure; inspection indicated that these weren't reversed coding errors but due to our assessment of heterogeneous learning dimensions.

4. Conclusion and discussion

We have developed a novel technology to better visualize networks that can be implemented as an effective teaching tool for education at the K-12 and undergraduate levels as well as for professionals working on analysis of multi-modal data, via two different prototypes. Our novel toolkit integrates embedded electronics with AR to help students/researchers interactively explore and understand different components of a network or a knowledge graph. Our toolkit uses 3D-printed nodes to visualize a network, with colored lights indicating each data modality and light flow in edges indicating direction of relationship between nodes. In our case study (tested on senior students enrolled in STAT 414 during Spring 2024 at Pennsylvania State University) we developed a remote where students can play with parameters of a probability distribution to visualize in real-time via superimposed AR how one distribution transforms to another in the network. Our case study shows statistically significant improvement in understanding of relationships between discrete and continuous probability distributions, post intervention. We observed good reliability (Cronbach alpha of 0.78) that should be interpreted as evidence of moderate coherence rather than strict unidimensionality. Additional support for construct validity was observed through differential learning gains across learner subgroups. Participants reporting lower or moderate subject-matter confidence demonstrated statistically significant improvement following the intervention. Furthermore, students who perceived the toolkit as engaging and useful also demonstrated greater improvement, suggesting alignment between learner interaction with the 3DPE/AR environment and the targeted educational outcomes. These findings should be interpreted as preliminary construct-validity evidence rather than definitive causal proof, particularly given the exploratory pre/post study design.

While 3D printing and AR/VR have been independently used to improve learning outcomes in undergraduate education [56–59], this is the first instance where embedded electronics is integrated with AR to better understand network graphs among undergraduate students and research professionals. In this study, we introduced an integrated embedded

electronics and augmented reality (AR) toolkit designed to enhance visualization and conceptual understanding of network graphs in educational and research settings. Unlike conventional 2D visualizations that often collapse complex interdependencies into dense, difficult-to-parse layouts, our approach externalizes relational structure into physical space while simultaneously augmenting it with dynamic virtual overlays. This hybrid tactile–digital representation supports interaction at multiple cognitive levels: spatial, visual, and parametric. Although the multi-modal nature of the tool could theoretically increase cognitive load, prior research in multimedia learning and cognitive load theory suggests that when modalities are coherently integrated and directly mapped to conceptual structure, they can reduce extraneous load and facilitate deeper schema construction rather than overwhelm working memory [60–62].

A key theoretical motivation for this work lies in embodied [41] and spatial cognition [63–65] frameworks, which suggest that learning is strengthened when abstract concepts are anchored to physical interaction and perceptual cues. Traditional 2D network graphs frequently become visually cluttered as complexity increases, limiting learners' ability to form stable mental models of structure and transformation. By distributing nodes physically and encoding directionality, magnitude, and modality through programmable LED flows and AR overlays, our toolkit reduces visual ambiguity while maintaining structural fidelity. The physical network acts as a stable spatial scaffold, while the AR layer enables dynamic parameter exploration without overwhelming the learner.

In the probability distribution case study, students demonstrated statistically significant improvements in objective knowledge immediately following the intervention. Importantly, gains were pronounced among students who reported low confidence prior to the intervention. This pattern suggests that multimodal visualization may be particularly beneficial for learners who struggle with abstract symbolic representations alone. While prior work has shown that immersive technologies can improve engagement [66–68], our findings suggest that the benefit extends beyond novelty effects to measurable conceptual gains in relational understanding.

Importantly, our contribution is not simply the use of AR in education. Rather, the novelty lies in integrating programmable embedded electronics with AR overlays to create a synchronized physical-virtual system. Existing AR educational tools typically operate entirely in virtual space, whereas physical manipulatives lack dynamic adaptability. Our system bridges this gap: the physical network externalizes topology, and the AR layer enables parameter manipulation, layered information, and scenario switching without reconstructing the physical model. This dual modality allows educators to maintain structural stability while flexibly exploring transformations.

The generalizability of this approach extends beyond probability theory or biomedical networks. Any domain involving relational or transformation-based structures, including systems biology, supply chains, knowledge graphs, and engineering systems, may benefit from a hybrid tactile–digital framework. However, replication across institutions with larger sample sizes along with testing for retention of this improved understanding in the long-term is necessary before broad educational claims can be made.

In summary, this work demonstrates that integrating embedded electronics with AR can serve as a viable multimodal teaching aid for complex network graphs. A strong impact appears among students with lower prior confidence, suggesting that such systems may help reduce abstraction barriers and promote conceptual equity in advanced STEM courses.

5. Limitations and future work

While our toolkit can effectively help communicate key components in a network graph, limitations still exist. Large network graphs can easily get very dense, and the current version of our toolkit cannot accommodate many data layers or nodes and edges simultaneously. For highly complex networks, we are looking at ways to scale this toolkit such that only a baseline set of pre-identified nodes will be 3D printed, and the remaining nodes and edges will be projected onto the virtual space. We are also looking to streamline our toolkit on GitHub such that anybody can download code to 3D print and

create their own physical network as well as the virtual overlay. Future work should investigate the time and expertise required for an educator to deploy a toolkit of this nature to build specific networks for visualization in their course.

Additionally, the study employed a single group pre/post design without a control group. Although improvements were statistically significant, we cannot definitively attribute gains solely to the toolkit rather than to increased instructional focus or repetition. Future work should incorporate randomized or quasi-experimental designs comparing this toolkit against traditional 2D visualization.

Furthermore, while multimodal systems can reduce abstraction barriers, they may also increase cognitive load if poorly implemented. Our design attempted to mitigate this risk by maintaining consistent color coding, limiting simultaneous active sub-networks, and mapping each interaction (e.g., parameter change) to a single clear visual response. Likewise, the design of the immersive interaction and the physical models were grounded in theories of embodied cognition and cognitive load theory, which suggests that multi-modal channels of information communication may reduce cognitive load assuming information is relevant to the topic at hand. Future studies should explicitly measure cognitive load and attention allocation to better understand how learners distribute perceptual resources across physical and virtual channels. This could be accomplished by leveraging the built-in eye tracking system standard in most head-mounted immersive displays. Color coding should also be modified with colorblind-friendly choices to accommodate a wider range of users.

Finally, and most critically for educators looking to integrate this intervention into their own curriculum, scalability of this educational intervention should be considered. From a scalability perspective, the current implementation uses a Microsoft HoloLens 2 device, which represents a non-trivial cost barrier and limits engagement with the interaction to one or two users at a time dependent upon available headsets. However, the core architecture of QR-based spatial anchoring and web-based remote control can be adapted to lower-cost smartphone AR platforms. The use of smart-phone based AR applications would significantly improve the scalability of such immersive interactions and reduce associated costs. In addition, future iterations may transition from dedicated hardware to modular kits with downloadable design files and cloud-based visualization engines to improve accessibility.

Declarations

Competing interests

The authors declare no competing interests for this study.

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Author Contribution

JK constructed the network for prototype 1 in Gephi, the physical model for prototypes 1 and 2, and drafted the manuscript; PD, CC, and AF constructed the virtual model for prototypes 1 and 2; PD also constructed the web interface (remote and viewer) for prototype 2; YV designed prototypes 1 and 2, collected data for the case study in STAT 414 class in Spring 2024, performed all statistical analysis and drafted the manuscript; JM, GM, and YV supervised the study. All co-authors were involved in writing the manuscript.

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None.

Data Availability

Videos demonstrating the use of our toolkit for prototypes 1 and 2 are included on FigShare https://figshare.com/s/bb58ee168d8dd1b81559?file=57347249https://figshare.com/s/d8882126b79da760676c?file=57363610 as well as in the Supplementary material. In addition, the links for the remote and viewer for prototype 2 are given below (trademarked to the corresponding author Veturi):https://cie.psu.edu/networkMR/distributions/remote.htmlhttps://cie.psu.edu/networkMR/distributions/viewer.html. The datasets generated and/or analyzed during the current study are not publicly available due to IRB constraints but are available from the corresponding author on reasonable request.

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Figures

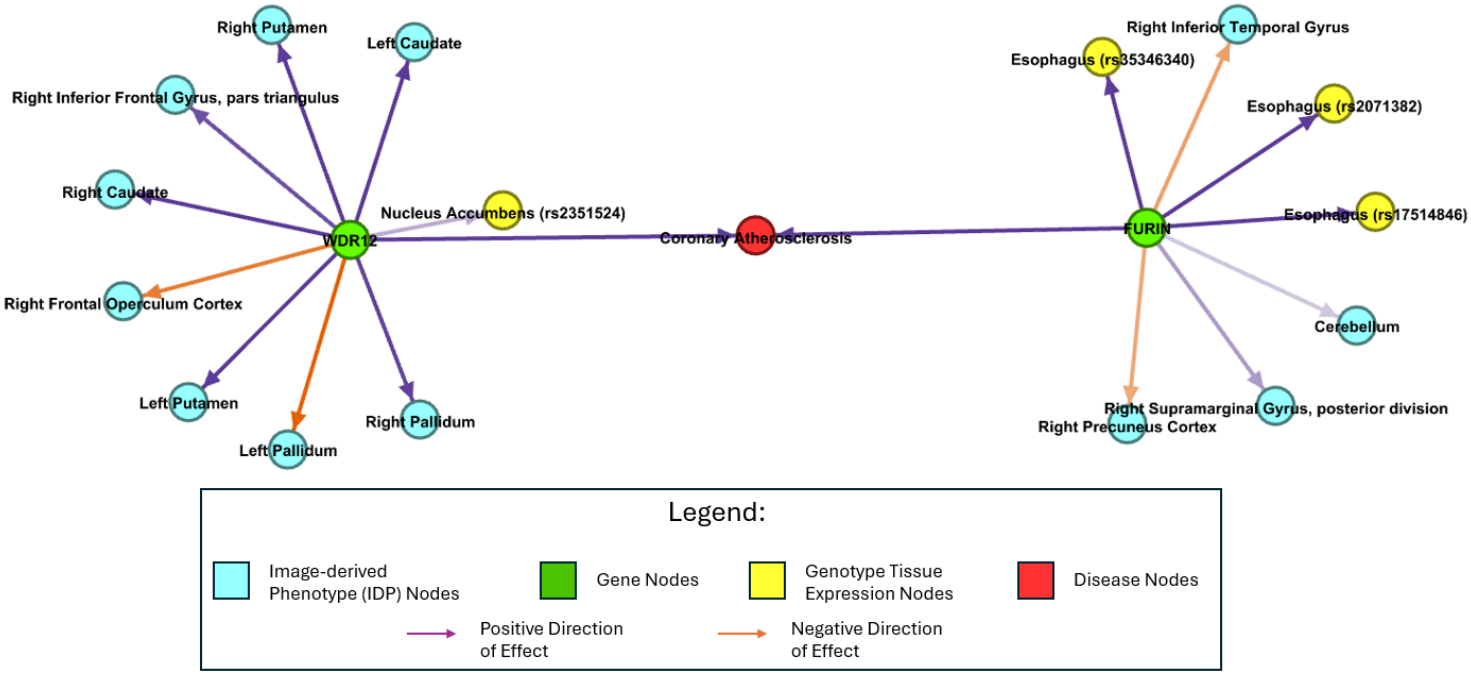


Figure 1

Genetic network generated with Gephi using the Yifan Hu layout algorithm. The legend was added using Microsoft PowerPoint, due to Gephi lacking a built-in feature.

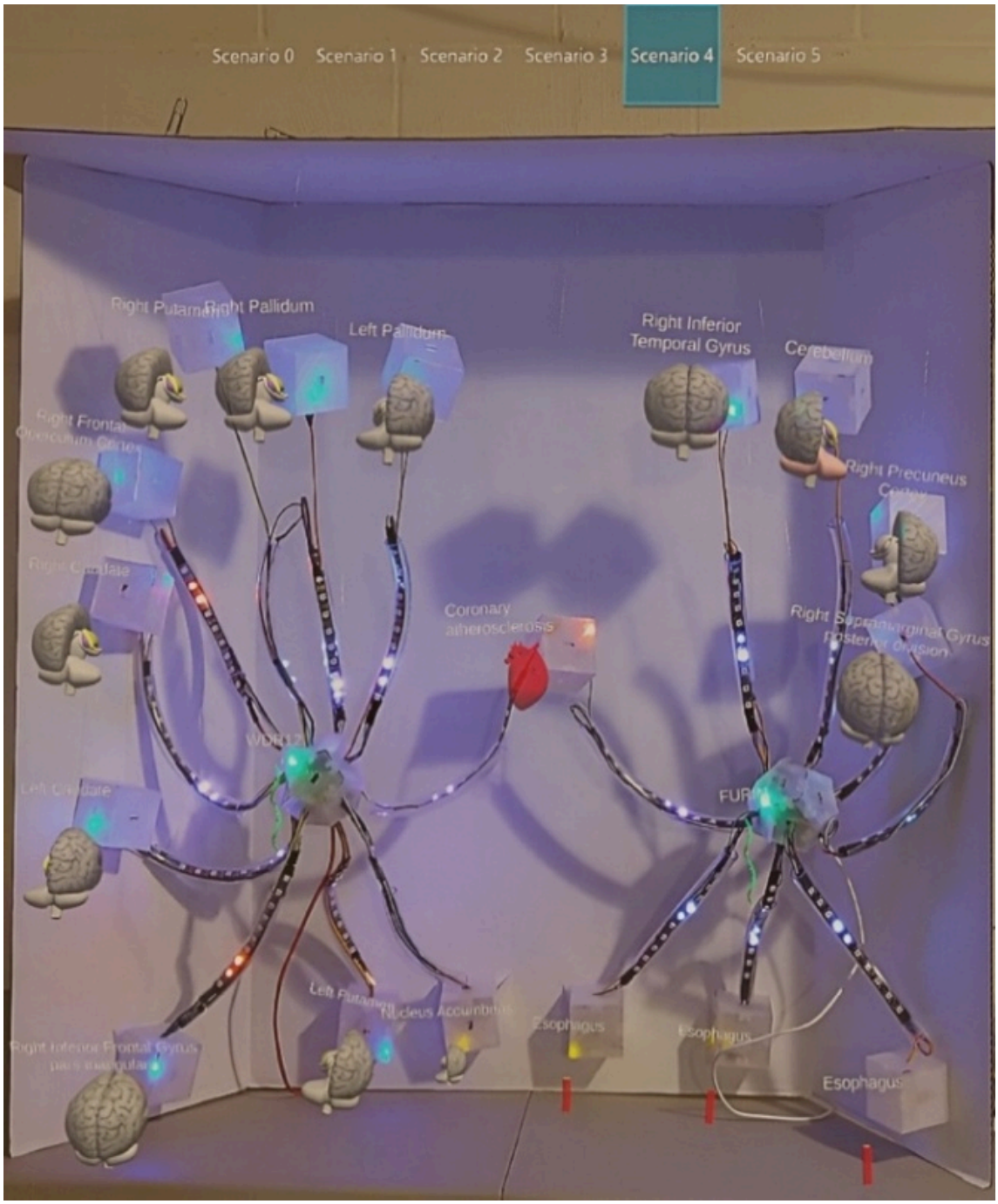


Figure 2

Overview of the multi-modal visualization (physical + virtual model) for scenario 4 in prototype 1. This scenario represents the complete network, so all nodes and edges are lit up.

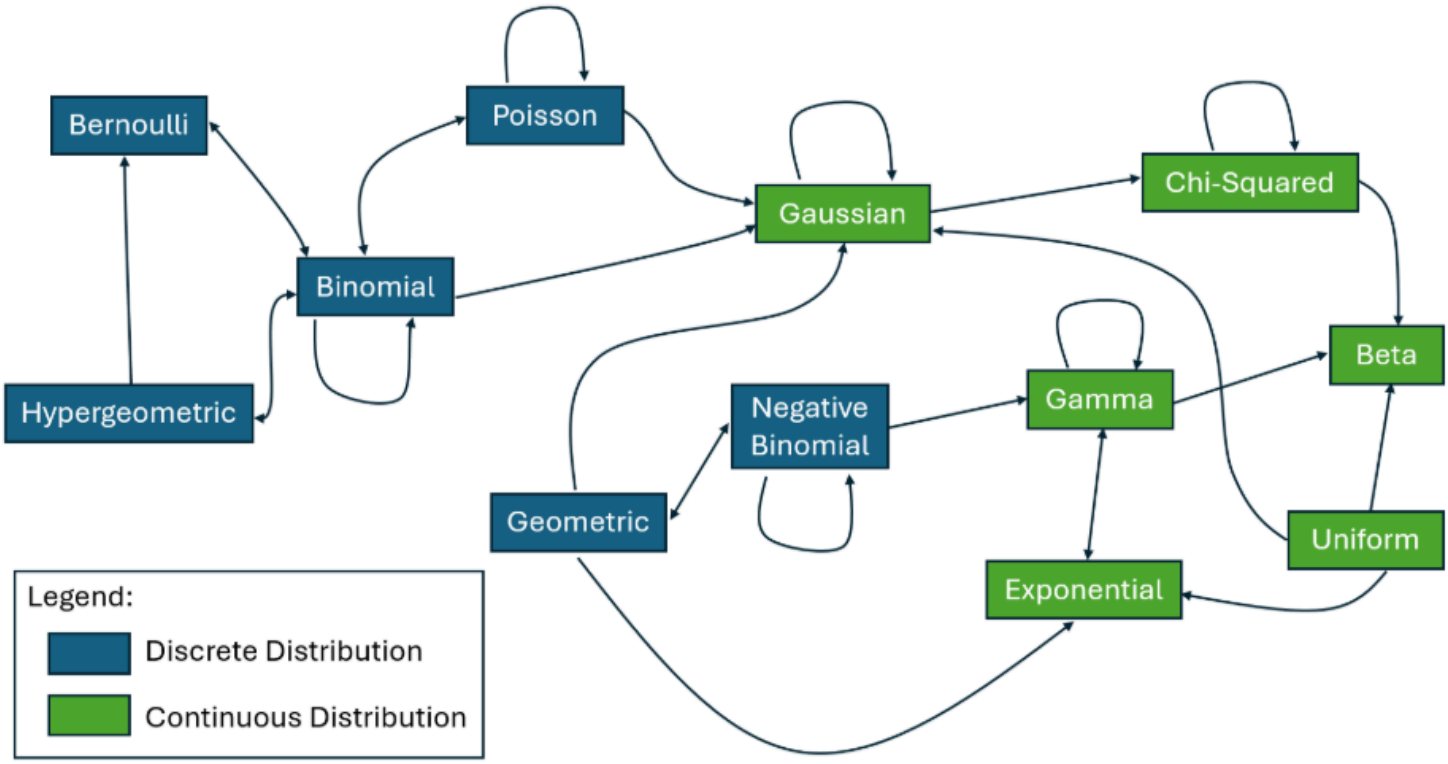


Figure 3

The probability distribution network graph developed for the case study. This figure was drawn using Microsoft PowerPoint.

a. Case Selection Menu

CASE 1: Taking the limit

CASE 2: Variable transformation

CASE 3: Conditioning

CASE 4: Convolution

CASE 5: Central Limit Theorem

CASE 6: Special cases

b. Scenario Selection Menu

Geometric --> Gaussian

Uniform --> Gaussian

Back

c. Parameter Selection Menu

Geometric --> Gaussian

Parameters of

$Geometric(X) = p$

$Gaussian(\bar{X}) = \mu, \frac{\sigma^2}{\text{sample size}}$

sample size : 5

$p : 0.25$

$\mu = \frac{(1-p)}{p}$

$\sigma^2 = \frac{(1-p)}{p^2}$

Back

Figure 4

Remote control web interface for probability distribution network graph. (a) Selection menu for cases. (b) Selection menu for scenarios. (c) Selection menu for parameters.

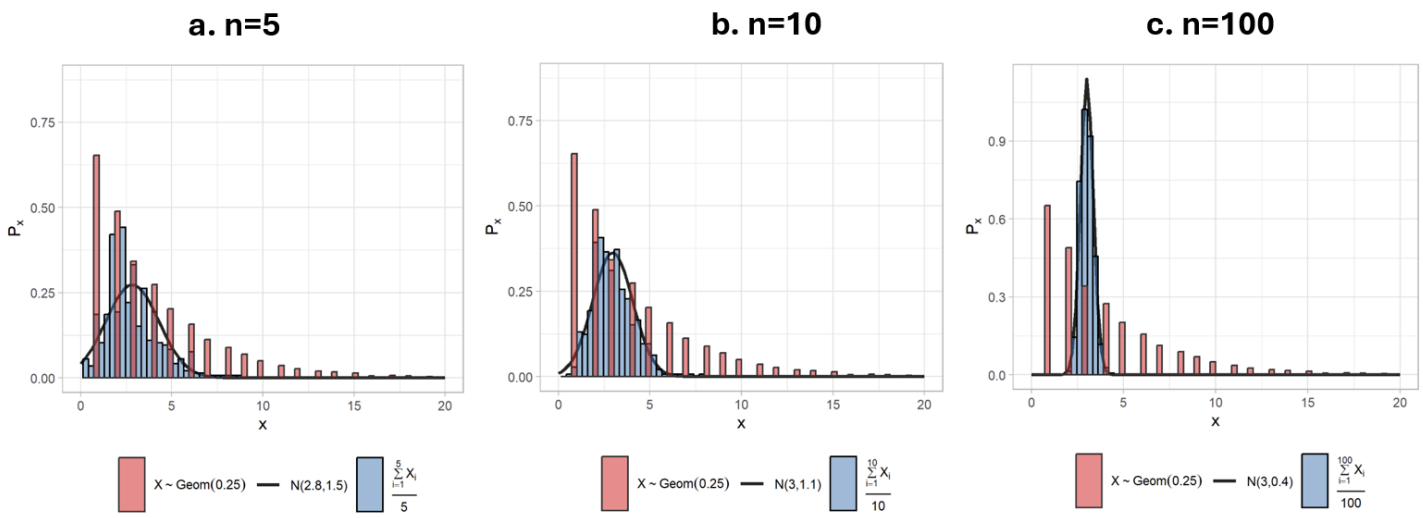


Figure 5

A plot of the source geometric distribution (in red) and the average of n geometric random variables (in blue) converging to the target Gaussian distribution (in black) due to the Central Limit Theorem. (a) n=5. (b) n=10. (c) n=100.

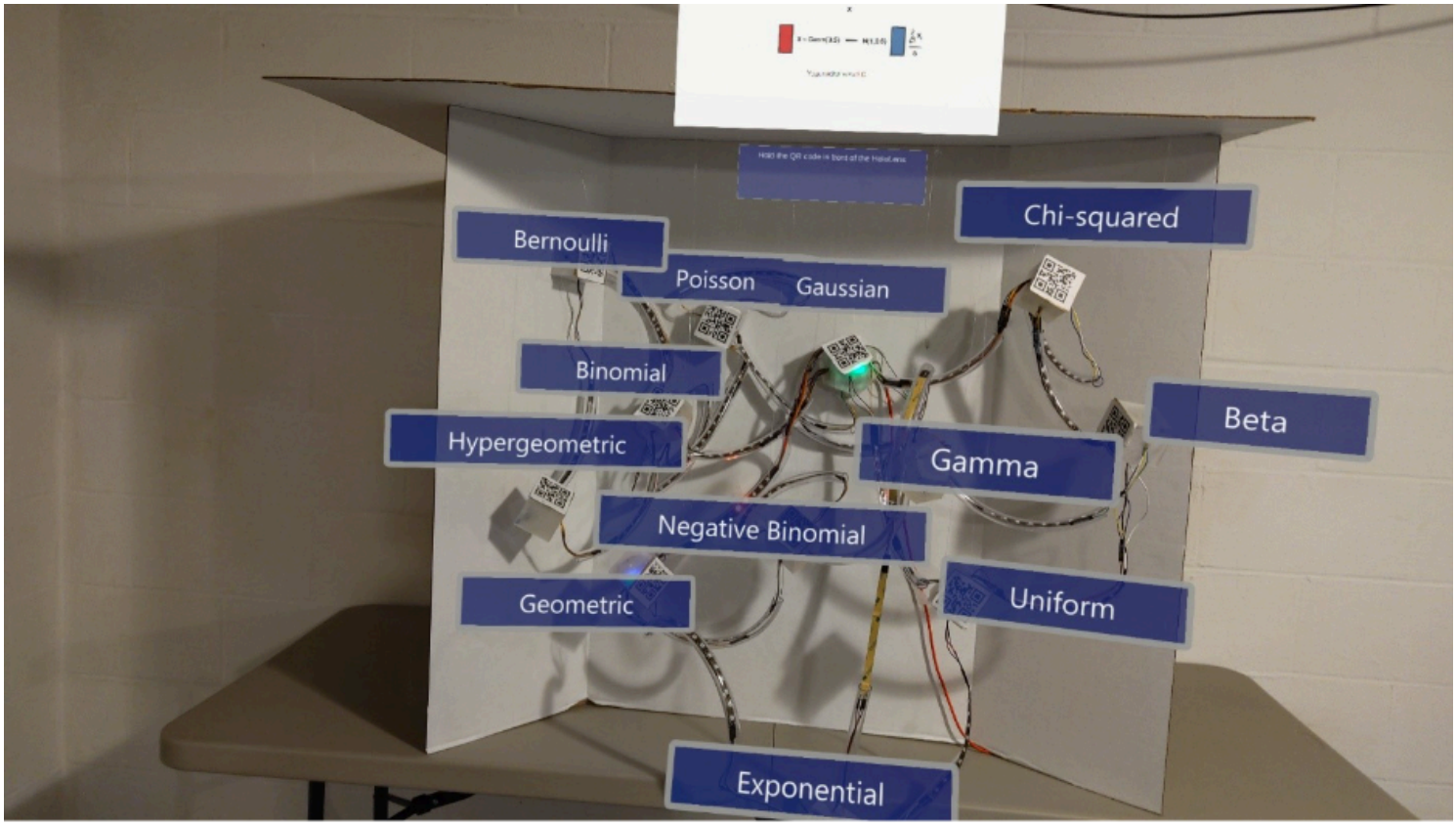


Figure 6

Integrated physical-virtual model of probability distribution network graph.

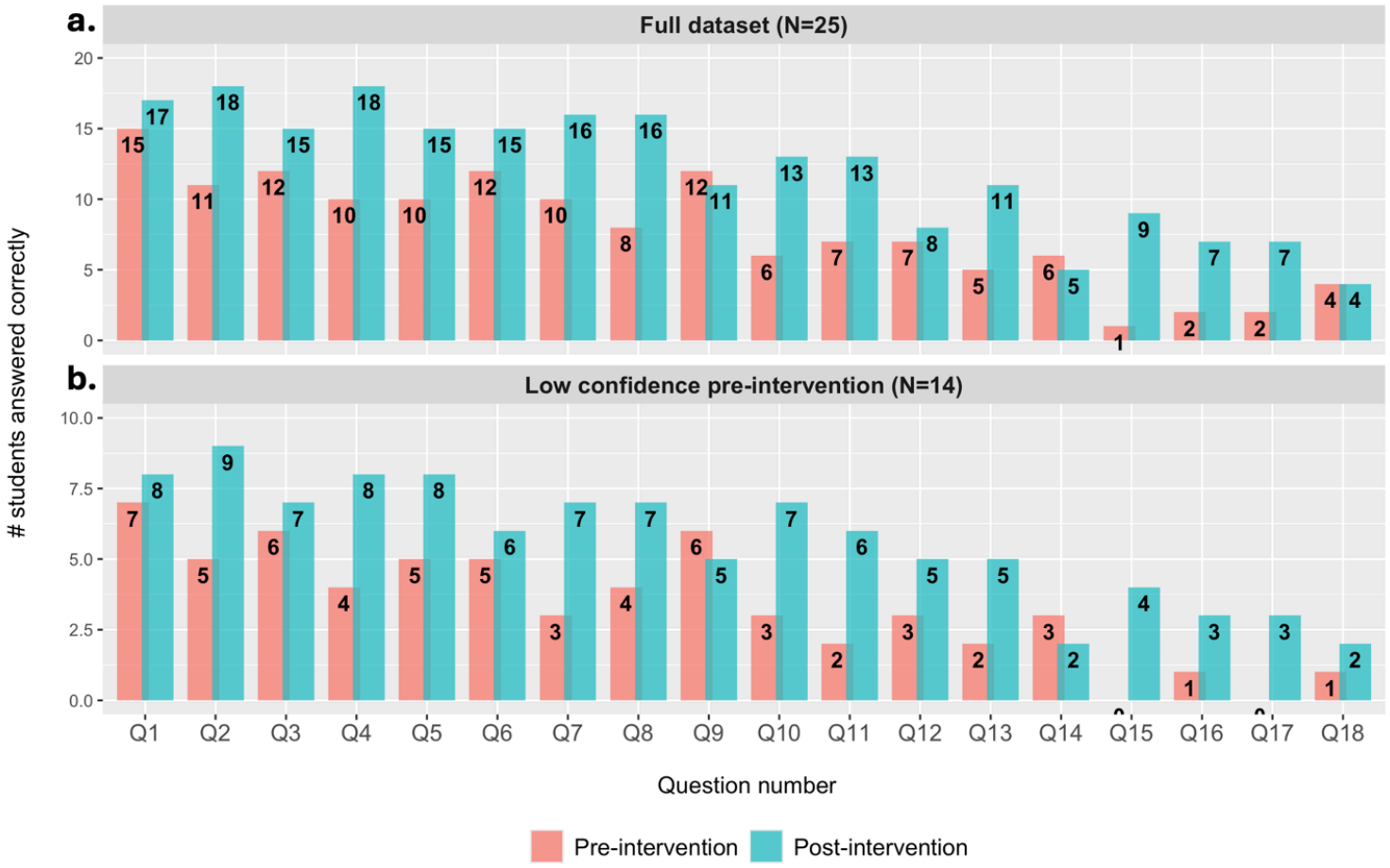


Figure 7

Number of students who answered each knowledge-based multiple-choice questions correctly before and after the intervention. (a) Results from the full dataset of students (N=25). (b) Results of students who indicated low confidence in subject matter (N=14).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Supplementary.docx