modular graph ($t(28) = 2.93, p = 0.007$, Pearson's correlation coefficient $r = 0.48$, 95% confidence interval: 0.15 to 0.72) and the lattice graph ($t(41) = 2.28, p = 0.027$, Pearson's correlation coefficient $r = 0.34$, 95% confidence interval: 0.04 to 0.58), but not significant for the random graph ($t(34) = 1.31, p = 0.2$, Pearson's correlation coefficient $r = 0.22$, 95% confidence interval: -0.11 to 0.51). Intriguingly, this pattern of results suggests that subjects can more easily learn the regular structure of modular and lattice graphs, and display slower reaction times when expectations are violated. We note, however, that the difference *between* the modular and lattice conditions and the random condition was not in itself significant (modular and random: Fisher's $z = 1.18$, one-sided $p = 0.12$, lattice and random: Fisher's $z = 0.55$, one-sided $p = 0.29$.)

Next, we tested whether certain graph structures facilitate learning more than others. We predicted that sequences generated by the modular graph would be the easiest for participants to learn, due to the graph's segregated meso-scale structure. As subject groups were exposed to different pairs of graph topologies, we performed three separate within-subject analyses using the data from Experiment 3. Each analysis examined a pair of graph types, with the order of exposure counterbalanced between subjects. For example, the first group was composed of (i) subjects first exposed to a stream of stimuli produced by a random walk on the lattice graph, followed by a stream of stimuli produced by a random walk on the random graph, as well as (ii) subjects first exposed to a stream of stimuli produced by a random walk on the random graph, followed by a stream of stimuli produced by a random walk on the lattice graph. In the same manner, the second group corresponded to modular/lattice, and the third group corresponded to modular/random. We separately fit a mixed effects model to each group. We found that the modular graph elicited significantly quicker responses than both the lattice (linear mixed effects model; $t(70) = 2.35, p = 0.022$; expected difference of 34.89 ms; 95% confidence interval: -44.49 to -4.02) and random ($t(69) = 3.429, p = 0.001$; expected difference of -34.89 ms; 95% confidence interval: -54.82 to -14.95) graphs (Fig. 3D,E). We did not find a significant difference between the lattice and random graphs ($t(68) = 1.48, p = 0.14$; expected difference of 12.85 ms; 95% confidence interval: -29.88 to 4.17). Models are summarized in Supplementary Table 5. These findings support the hypothesis that the presence of meso-scale structure in modular graphs impacts learnability.

In a final set of analyses, we investigated the extent of the influence of graph structure on learning. More specifically, we tested whether smaller scale topological features or larger scale topological features might also impact learning, in addition to the meso-scale features studied in the previous section. First, we studied smaller scale topological features using degree, a summary statistic of a node's neighborhood defined by the number of edges emanating from a node. Second, we examined large scale topological features using betweenness centrality, which intuitively captures a node's role in mediating long distance traversals through the graph, and which is defined by the fraction of shortest paths that pass through a given node (Fig. 4A). We studied the