Let us calculate first the estimate of our simplified version of expectation:

$$\mathbb{E}_{q_\psi(\mathbf{z}|x^l)}[f(\mathbf{z})] = \mathbb{E}_{p(\boldsymbol{\epsilon})}[f(g(\boldsymbol{\epsilon}, x^l; \psi))] \approx \frac{1}{n}\sum\nolimits_{i=1}^{n} f(g(\boldsymbol{\epsilon}^i, x^l; \psi)) \tag{1}$$

Then we obtain for our loss function the following approximation:

$$\begin{aligned} ELBO(q_\psi(\mathbf{z}|x^l)) &= \mathbb{E}_{q_\psi(\mathbf{z}|x^l)}[log(p_\theta(x^l|\mathbf{z}))] - D_{KL}(q_\psi(\mathbf{z}|x^l)||p_\theta(\mathbf{z})) \\ &\approx \frac{1}{n}\sum\nolimits_{i=1}^{n} log(p_{\hat{\theta}}(x^l|g(\boldsymbol{\epsilon}^i, x^l; \psi))) - D_{KL}(q_\psi(\mathbf{z}|x^l)||p_\theta(\mathbf{z})) \end{aligned} \tag{2}$$

If in some cases the Kullback-Leibner Divergence is not computable we can take take the Monte Carlo Estimate of the entire loss function:

$$\begin{aligned} ELBO(q_\psi(\mathbf{z}|x^l)) &= \mathbb{E}_{q_\psi(\mathbf{z}|x^l)}[log(p_\theta(\mathbf{z}, x^l))] - \mathbb{E}_{q_\psi(\mathbf{z}|x^l)}[log(q_\psi(\mathbf{z}|x^l))] \\ &\approx \frac{1}{n}\sum\nolimits_{i=1}^{n} log(p_{\hat{\theta}}(x^l, g(\boldsymbol{\epsilon}^i, x^l; \psi))) - log(q_\psi(g(\boldsymbol{\epsilon}^i, x^l; \psi)|x^l)) \end{aligned}$$