Prevalent matrix completion methods capture only the low-rank property which gives merely a constraint that the data points lie on some low-dimensional subspace, but generally ignore the extra structures (beyond low-rank) that specify in more detail how the data points lie on the subspace. Whenever the data points are not uniformly distributed on the low-dimensional subspace, the row-coherence of the target matrix to recover could be considerably high and, accordingly, prevalent methods might fail even if the target matrix is fairly low-rank. To relieve this challenge, we suggest to consider a model termed low-rank factor decomposition (LRFD), which imposes an additional restriction that the data points must be represented as linear, compressive combinations of the bases in a given dictionary. We show that LRFD can effectively mitigate the challenges of high row-coherence, provided that its dictionary is configured properly. Namely, it is mathematically proven that if the dictionary is well-conditioned and low-rank, then LRFD can weaken the dependence on the row-coherence. In particular, if the dictionary itself is low-rank, then the dependence on the row-coherence can be entirely removed. Subsequently, we devise two practical algorithms to obtain proper dictionaries in unsupervised environments: one uses the existing matrix completion methods to construct the dictionary in LRFD, and the other tries to learn a proper dictionary from the data given. Experiments on randomly generated matrices and motion datasets show superior performance of our proposed algorithms.