The classical literature on streaming algorithms has mainly studied two types of algorithms: randomized and deterministic. However, almost all classical analyses of randomized streaming algorithms assume that the stream is "fixed in advance", making them unfit for use in adaptive settings where future stream updates depend on previous outputs of the algorithm. Meanwhile, deterministic algorithms are guaranteed to work in adaptive settings, but many important problems in the streaming literature do not admit efficient deterministic algorithms. This raises the question of whether one can enjoy both worlds: do there exist robust randomized streaming algorithms, which are space-efficient and provably work in adaptive settings? The recent couple of years have seen a surge of work on this topic, starting from a generic robustification framework we developed, which turns "standard" randomized algorithms into robust ones. As it turns out, the answer to the above question is largely positive for insertion-only streams, but still unknown in general turnstile (insertion-deletion) streams. I will present our framework and mention several lines of follow-up work on this topic, including improved frameworks, results for specific algorithms, and connections to a wide range of topics within computer science, including differential privacy, cryptography, learning theory and others. Focusing on classical problems such as distinct elements counting and norm estimation, I will highlight what we know in the turnstile setting and present several directions for future work. Based in part on joint works with Rajesh Jayaram, David Woodruff, and Eylon Yogev, and with Talya Eden and Krzysztof Onak. (I will also briefly mention related joint works with Noga Alon, Yuval Dagan, Shay Moran, Moni Naor, and Eylon Yogev.)