Dear Search Committee Chair,

I am delighted to write this letter on behalf of Vineet Kumar, who earned his PhD under my supervision at Carnegie Mellon and is now applying for a tenured faculty position at your institution. Over the course of his doctoral training, Vineet distinguished himself as a scholar of rare caliber—demonstrating intellectual independence, methodological rigor, and a keen commitment to advancing the frontiers of quantitative marketing, studying topics involving the digital economy and business models. I have had the privilege of witnessing first‑hand not only his extraordinary intellectual gifts, but also the breadth, independence, and impact of his scholarship for well over a decade.

Vineet’s research has been both deep and broad. He has produced a series of influential papers that have reshaped how we understand digital business models, covering topics such as open‑source ecosystems, digital transformation strategies, subscription and product strategies including versioning like freemium, bundling, and also network effects. All of these are of particular importance in the digital economy that enables novel business models (perhaps less so with typical packaged goods).

Vineet excels in both the rigor of quantitative models theoretically grounded in economics and the generality and flexibility of machine‑learning algorithms—two intellectual traditions that have historically been seen as distinct, or seemingly incompatible ways of thinking. One approach, often based in economics, values human domain knowledge and theory to build models, while not focusing as much on predictive capability. A very different approach, based in machine learning and computer science, develops models that are mostly atheoretical and domain independent, relying only on data. The advantage here is that these models are empirical first, and more capable, but often lack transparency and explainability. Vineet has used his training in both economics and in machine learning to build a bridge between two disciplines, which I think is very impressive and unique. I’d like to highlight his research with one example from each domain, first involving structural econometric models, and second, with machine learning models.

In the paper on “*The Dynamic Effects of Bundling as a Product Strategy,”* Vineet examines the long-term impact of bundling hardware and software products. Bundling is one of most important product and pricing options for firms, and is very flexible, since it can be easily used in almost any setting. Earlier work emphasized how bundling exploits negative correlations in consumers’ static valuations, but has not considered how dynamics and intertemporal tradeoffs impact the effectiveness of bundling. Vineet develops a model based on rich and carefully thought out consumer preferences for products and bundles, and estimates the model with data from videogame consoles, bundles and games. The research has several important and unique aspects that are noteworthy. First, in a dynamic setting the sequence of purchases and timing plays an important role. Consumers first purchase a unit of hardware, and then purchase potentially several different software products over time. Developing a tractable, yet realistic model in the presence of dynamics is quite a challenge. Second, the model incorporates expectations about both hardware and software markets within a structural framework—an innovation since it is the first empirical model to integrate these distinct, yet related markets. Third, since the effectiveness of bundling is driven by correlation in consumer valuations across products, it is critically important to ensure clear identification of this model element. Vineet uses a clever methodological innovation, leveraging the tying ratio (ratio of software sales to hardware installed base) as a means of identification, which is possible here because one hardware unit (console) can support many software units (games), thereby allowing precise inference of valuation correlations.

The empirical content of the research and the associated counterfactuals are also very interesting and relevant to both researchers and practitioners. First, bundles are shown to increase overall volume and shift the consumption timeline, an outcome that depends on the larger installed hardware base engendered by earlier purchases. Second, a mixed bundling scheme outperforms a pure bundling arrangement. Third, the research reveals that a stronger positive correlation between hardware and software valuations yields higher sales via the same dynamic mechanism. The paper diverges from the conventional static view, which posits that bundling is more effective under negative correlation, and finds that with dynamics, positive correlation can be more effective, since it intensifies the purchase advancement effect. Finally, the paper establishes that bundling’s efficacy diminishes when indirect network effects intensify—a result that was unknown. The implications are profound for any market where dynamic considerations shape consumer behavior, offering a richer, more rigorous foundation for designing bundling policies.

Having provided a sense of Vineet’s thoughtful approach in his structural work, let me walk through his more recent research bridging theory with machine learning models. By bringing in theory to guide the learning in machine learning models, Vineet is able to achieve multiple goals across projects.

First, let me describe one of the big advances in human understanding of visual product characteristics that Vineet studies in *“Generative Interpretable Visual Design”*. Visual design of products are important for consumers and marketers, yet, studying them in a tractable manner has proven challenging. While we can compare two visual designs, determining interpretable visual characteristics that taken together characterize the complete visual design has proven a formidable challenge. This is a necessary steps towards solving important problems like visual recommender systems, visual conjoint or understanding competition in visual design characteristics. This research aims to automatically obtain and quantify interpretable visual attributes of products, as well as to generate new counterfactual visual designs.

Visual appearance is inherently high‑dimensional and difficult to interpret. Existing literature either relies on human expertise or uses non‑interpretable features (e.g. from PCA-like models). In contrast, Vineet’s theory‑driven disentanglement methodology discovers and measures visual characteristics automatically, without requiring expert intervention. Theory is integrated into the framework in two critical ways: first, by defining an objective function that encourages low‑dimensional, orthogonal representations grounded in product design properties; second, by exploiting the idea that products belonging to a brand exhibit distinct brand‑specific “visual signatures” (e.g., Audi automobiles). Vineet leverages the information inherent in marketing variables (e.g. brand and price), and its correlation with visual appearance in a uniquely original way. The machine learning approaches in the literature just use the image data and perform unsupervised learning, or would require a prohibitively expensive human labeling exercise. Vineet instead transforms the problem from an unsupervised one with just images to a supervised one with both images and brand (as an example). This transformation helps overcome a well-known challenge in the machine learning literature called the “impossibility theorem,” that makes purely unsupervised learning unsuitable for disentanglement. Further, the methodology facilitates the automatic generation of counterfactual visual designs in a controllable manner, constituting a significant advancement previously deemed unattainable.

Next, let me provide another excellent example of briding theory with machine learning, using Vineet’s paper on "*Nonparametric Pricing Bandits Leveraging Informational Externalities to Learn the Demand Curve.*" In this paper, he tackles the challenging problem of learning an unknown demand curve (for a new product), which can then be used to determine optimal prices, for instance. Typically, firms have experimented to learn about the demand curve, which can be quite inefficient. Reinforcement learning with multi-armed bandits can be very useful in these settings, but such models are fragile, as seen with benchmarks. Vineet connects microeconomic theory using the very simple idea that demand curves are downward-sloping to reinforcement learning. While the goal is simple, It turns out that incorporating microeconomic theory nonparametrically without any functional form is quite a challenge. To see this, imagine the space of all functions that span a range, and then it is possible to see how restricting it to the set of monotonic functions is not very tractable. The impressive aspect of the method is that it not only improves the performance of the bandit, but provides guarantees on the resulting learned demand function to ensure theoretic consistency. As we are moving towards algorithmic pricing in many industries, this approach will become necessary to avoid fragile algorithms and provide robustness that comes from theoretical grounding.

Overall, as you can see, Vineet takes on deep technical challenges in his research, where overcoming challenges helps answer important practically relevant questions, whether it is in designing product and pricing strategies, in pricing algorithms that offer guarantees, or in obtaining human interpretable visual product characteristics. I am highly bullish on his uniquely valuable theoretically grounded research approach, and fully expect that such methods will be beneficially used across a wide class of future problems in marketing and business more generally.

Vineet is the rare scholar who is exceptionally well-trained in both economics-based methods, as well as machine learning based methodologies from computer science. These two methodological views form the foundations for much of the cutting-edge research in quantitative marketing. His training in econometrics is top-notch, with exceptional performance starting with his doctoral studies during his time at Carnegie Mellon, and continuing on throughout his career as a faculty member. His training in machine learning from the school of computer science at Carnegie Mellon featured advanced classes by the leaders in machine learning, including Tom Mitchell, who wrote on of the foundational textbooks in the field, and who served as dean of the school of computer science at CMU. In fact, Vineet even helped contribute to the second edition of the textbook, which Tom acknowledged in the new edition.

Vineet has clearly distinguished himself in mentoring, advising and working with doctoral students and continuing with junior faculty. In fact, in and around his cohort, I cannot of think of many others who have achieved this as well. He has served as primary advisor for 4 PhD students, and these research efforts have received multiple awards from INFORMS Society of Marketing Science, MSI Adam Clayton, and American Statistical Association. He has undertaken a high-involvement but worthy initiative in developing these junior scholars, and his students have been placed at highly regarded research universities, including Cornell, Columbia, Purdue and the National University of Singapore. His trainees routinely credit his mentorship with helping shape their intellectual trajectories. I fully expect that he would only grow his contributions to both his institution and more broadly our academic field with his mentoring in the future.

Vineet teaches two courses, AI Strategy and Marketing and Digital Strategy, that he teaches to Yale MBA and Masters students. Both of these are courses he has developed, and highly related to his research interests. He is excellent in the classroom, and is well known for his discussion-based approach to learning. I find it gratifying that he also brings in accessible research papers into the classroom as translation opportunities for advanced learning in these fast evolving areas.

The combination of Vineet’s research depth, methodological innovation, and collaborative spirit makes him an ideal candidate for a tenured faculty role. He is poised to serve as a bridge between traditional quantitative marketing and newly developing areas in machine learning, including generative AI. I envision him fostering cross-disciplinary collaborations that are increasingly relevant in today’s research environment. His track record suggests that he will attract and mentor doctoral students and junior faculty, and contribute to shaping curricula that prepare graduates for the future era.