



# Distinguishing unpredictability from uncertainty in entrepreneurial action theory

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**Abstract** The traditional view that perceived and archival uncertainty measures are substitutable proxies for “true” environmental (entrepreneurial) uncertainty presumes an “all-seeing eye.” Adopting a representationalist epistemology, we distinguish environmental (objective) unpredictability from entrepreneurs’ subjective uncertainty, which has so far been theoretically confounded. It is, in fact, possible for an entrepreneur to be highly certain despite excessive unpredictability and vice versa. Theoretically distinguishing these constructs has fundamental implications for entrepreneurial action theory. For example, because intentional action is consciously originated, unpredictability influences action only indirectly, while uncertainty has direct effects. Outcomes, on the other hand, are directly affected by the complexity and dynamism (unpredictability) of things, whereas uncertainty only has an indirect and tenuous role in what occurs. We develop hypotheses along these theoretical lines and test them on a longitudinal sample of new mobile apps and survey responses from their developers. We find, generally, that unpredictability, uncertainty, and their effects on

entrepreneurial action are empirically distinct. This provides added impetus for a shift away from positivism and toward a subjectivist approach to entrepreneurship.

**Plain English Summary** Distinguishing Unpredictability from Uncertainty in Entrepreneurial Action Theory. Entrepreneurship scholarship commonly references a single “entrepreneurial uncertainty” construct in discussing the effects of the unknown on entrepreneurial action. We explain that there are not one but *two* key constructs at play that should not be confounded: external unpredictability and subjective uncertainty. We explain, and support with evidence from the app development industry, that the unpredictability of a market environment or of entrepreneurial outcomes only has indirect influence on actions. It is the entrepreneur’s own uncertainty that drives what actions they will pursue. However, the outcomes that result from action are causally tied to the real unpredictability of the market rather than the entrepreneur’s uncertainty of it. As we move into the theory refinement stage of the entrepreneurship discipline, greater care must be taken in referencing one or the other (or both) in entrepreneurship theory.

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## 1 Introduction

Uncertainty is one of the most central themes in entrepreneurial action theory—uncertainty is typically understood as a necessary condition for entrepreneurship. Broadly speaking, entrepreneurship scholars have developed and attended to a single *entrepreneurial uncertainty* construct that has been derived as, essentially, a special case of environmental uncertainty. Environmental uncertainty, which has long been of interest within strategic management (Child, 1972; Duncan, 1972; Lawrence & Lorsch, 1967; Pfeffer & Salancik, 1978; Tushman & Nadler, 1978), is defined by Tosi et al., 1973: 30) as “the degree of accuracy with which one can predict the future.” It is entrepreneurial uncertainty when the context of the predictions pertains to an entrepreneurial endeavor—it is uncertainty derived from the “entrepreneurial environment” (McKelvie et al., 2011). Entrepreneurship also inherited from strategic management, along with this definition, an unsettled debate about how uncertainty is best measured—i.e., whether it is better captured as a compendium of archival measures of its causes (e.g., complexity, dynamism, munificence) or as a subjective measure of how it is perceived by actors (Buchko, 1994; Dess & Beard, 1984; Downey & Slocum, 1975; Howell & Burnett, 1978; Lorenzi et al., 1981; Tosi et al., 1973). Scholars in favor of the archival environmental uncertainty (AEU) measure argued that it was more direct and objective (Dess & Beard, 1984; Snyder & Glueck, 1982; Tosi et al., 1973), while scholars who favored the perceived environmental uncertainty (PEU) metric argued that it is perception that matters more to behavior (Anderson & Paine, 1975; Kreiser & Marino, 2002). While this debate never concluded, entrepreneurship scholars have tended toward PEU measures due to their direct relationship with entrepreneurial action (e.g., Freel, 2005; Liao & Gartner, 2006; McKelvie et al., 2011), although some have used AEU measures (e.g., Baum et al., 2001).

We will argue that this traditional entrepreneurial uncertainty construct is premised upon an overly strong assumption that perception can be *veridical*, i.e., that it is objective and complete (Felin et al., 2017). Perceptions that are not veridical, that are less than a fully accurate reflection of reality in toto, are presumed “irrational” (Ariely, 2008). Perceptual oversights—such as the famous gorilla in the midst of a foray of basketball

passes (Simons & Chabris, 1999)—are understood to be cognitive errors, a “blindness to the obvious” (Kahneman, 2011). Koenderink (2014) dubs this assumption the “all-seeing eye.” In contrast, Felin et al. (2017) note that perception always involves and entails a large and significant *subjective* component—perception is *intentional* and, thus, directed (Seth & Hohwy, 2021). Because perceptive capacity is scarce, such directedness is always and only *subjectively rational* (Packard & Bylund, 2021), pointing awareness toward those percepts that are deemed most pertinent. In the case of the Simons and Chabris (1999) experiment, judging an actor to be in error for missing the “obvious” gorilla when under clear instructions to count the number of passes is a theoretical mistake. While these arguments have so far received mixed reviews (see Chater et al., 2018), their implications should be considered. If we accept perception as at least partially subjective, intentional, and directed, then perceptions of reality must be theoretically distinguished from reality per se. Specifically, it implies that reality’s influence over behavior is *mediated* by its perception and representation, which is, itself, moderated by subjective intention.

If correct, then the entrepreneurial uncertainty construct must be theoretically partitioned into two: what we will call *objective unpredictability* and *subjective uncertainty*. Objective unpredictability references the knowability of some future outcome (e.g., venture performance), while subjective uncertainty references the doubts that one experiences about the outcome. Our main argument is that these are not, theoretically, synonymous. Although they often correlate (Lueg & Borisov, 2014), this need not be the case, especially within the entrepreneurial context. We thus make two foundational contributions to entrepreneurial action theory. First, we argue that a theoretical separation of ontological states of affairs and their epistemic perceptions (McBride & Packard, 2021; McBride & Wuebker, 2022) is necessary for a coherent entrepreneurship science. We offer *representationalism* as a preferred meta-theoretical foundation that avoids assuming perception to be veridical. Second, we elaborate the implications of representationalism for entrepreneurship theory, specifically in terms of the distinctive nature of unpredictability versus uncertainty with respect to entrepreneurial action.

We support our contributions empirically by testing this representationalist framework in the context of app

development. Our results offer strong support for representationalism and for the theoretical separation of the subjective uncertainty and objective unpredictability constructs. We conclude by discussing why this partitioning is consequential for entrepreneurship theory and for all theories where uncertainty is predicted to influence phenomena of interest. In short, we reject the “all-seeing eye” that would have us study entrepreneurship as some “outside observer.” If we cannot see through some all-seeing eye, we are left with the eyes of entrepreneurs themselves as the best vantage for observing entrepreneurial phenomenon.

### 1.1 Perception in entrepreneurial action theory

Entrepreneurial action theory is an “umbrella” theory that is “broadly concerned with the decision to take action toward entrepreneurial endeavors under conditions of uncertainty” (Wood et al., 2021: 148). These “conditions of uncertainty” draw our attention here. A lack of foundational clarity has, we will argue, led to difficulties in pinning down what this “uncertainty” is and, thus, how it affects entrepreneurial action.

Uncertainty is an *epistemic* phenomenon—it concerns what is or is not known. Knowledge is commonly defined as “justified true belief,” the correspondence of a belief or “knowledge claim” to the reality that it purports to describe. But let us be careful here about the domain of *reality*. We adopt a narrow ontology where reality is confined to that which is ontologically objective and independent (Azzouni, 2017; McBride & Wuebker, 2022; Packard, 2018)—a “state of affairs” (Reinach, 1982) composed of the Kantian category “things in themselves”—which essentially excludes all but the physical or material realm only (including its unobservables). We reject both the categories of ontological dependence (i.e., that a thing becomes real if and when believed to be real) and epistemic independence (i.e., ideas or concepts that exist independent of human minds<sup>1</sup>). Thus, we also reject

<sup>1</sup> As King (1999) explains, the concept of epistemic emergence in realism cannot coherently rid itself of epistemic dependence. It may be true that an ‘emergent’ social institution cannot be reduced to a single individual. But that an institution is independent of a single individual does not make it epistemically independent, i.e., independent of *all* individuals. The litmus test for epistemic independence must be whether it can survive the absence of all minds. For example, institutional constraints that impede an individual’s will are, and should be understood as, constraints imposed on that individual by *others* collectively.

the tendency among subjectivists to depict reality per se as (at least partially) subjective or epistemic (e.g., Koenderink, 2014), which “comes across as somewhat confused, as ontology is, by definition, the domain of reality. That something could be “real” in a non-ontological sense is, of course, paradoxical” (Packard, 2017: 540; 2018).

The “phenomenal” or “epistemic” realm of thought, however, is the domain of perception and understanding and is much broader than our narrow ontological domain. Philosophers have debated the nature of perception and the origins of knowledge for millennia. The prevailing view is *representationalism*<sup>2</sup> (Chalmers, 2004; Fodor, 1981; Hoffman, 2000), which holds that there is no direct perception, but that what one perceives is a mental representation generated by the mind from sensory inputs. Metaphorically, we experience reality as a movie, produced and directed by our minds, from a script provided by sensory stimuli. It is this representation that is consciously “perceived.” This theory of perception has the advantage of easily explaining illusion (e.g., hallucinations, mirages) as well as the capacity to have extrasensory experiences (through mental simulation). The possibility of error in the representational process implies that what one perceives is not always or necessarily what there is. Some have argued that it never is (e.g., Hoffman & Prakash, 2014).

But confusion arises when adopting a realist social ontology—i.e., the position that social phenomena are ontologically real and objective—and a correspondingly strong empiricist epistemology that supposes direct and complete (“veridical”) perception. This position, even if only implied, remains widespread in the social sciences, including entrepreneurship. But it leaves us with an “all-seeing eye” problem.

### 1.2 Entrepreneurship’s all-seeing eye

While behavioral economics has pushed against standard economics’ artificial notion of a perfectly rational *homo economicus*, it replaces this omniscient

<sup>2</sup> Chia (1996) offers a “postmodern” critique of representationalism, much of which we agree with. However, the representationalism that Chia attacks is not the theory of perception and cognition that we attend to here, but a more extensive “representationalist” (we would call it ‘realist’) metaphysics.

actor with scientific omniscience (Felin et al., 2017). That is, action is presumed to be inefficient (i.e., irrational) if it departs from what the actor *should* know and understand as optimal behavior (Packard & Bylund, 2021). Thus, it presumes a “perceptual omniscience” (Felin et al., 2017: 1043) as a different, but still unrealistic, standard against which human action is judged to be rational or not.

### 1.3 Uncertainty’s all-seeing eye

This “all-seeing eye” underpins the modern construct of entrepreneurial uncertainty too. Uncertainty is understood to be an “objective unknowability, existing in the environment, about potential outcomes and the probability distributions on possible outcomes from actions” (Miller, 2012: 60). Entrepreneurial uncertainty is, in this sense, an objective unknowability about entrepreneurial outcomes, an ontologically objective construct that has real effects on actors.

Some have distinguished uncertainty in terms of its internal versus external sources (e.g., Kahneman & Tversky, 1982), i.e., external uncertainty exists where the culprit is some external obfuscation that impedes predictability, while internal uncertainty exists where it is some internal capability deficiency to blame. This distinction, from the purview of prevailing realist-empiricist meta-theory, is merely semantic. One would generally say that a coin flip is externally uncertain, i.e., that the reason that it is unpredictable is that its disposition is toward two outcomes of equal likelihood given the dynamism of its flipping. But we can also correctly assert that this disposition is *internal*, i.e., that it is due to the ignorance of the observer, and not to some innate indeterminism (Packard & Clark, 2020b); if we could eliminate the internal ignorance by measuring and accounting for all factors of the coin’s flipping, we could precisely calculate its outcome every time. The distinction between internal and external uncertainty, then, is not a true difference in the nature of uncertainty—they are, in fact, the same (this is the Bayesian view; see Cyert & DeGroot, 1987)—but only in the pragmatic attribution of uncertainty to what is to blame for the ignorance using a standard of reasonableness. Because it would be unreasonable to expect one to precisely know all factors necessary to calculating the outcome of the coin flip in a typical circumstance, we would

not blame the individual for their ignorance but the situation itself.<sup>3</sup>

Realism thus implies a single “true uncertainty” for any situation, which comprises all factors that inhibit the predictability of some future state. This uncertainty imposes upon actors’ consciousness, altering their actions.

To study these effects, scholars have measured this “true” or “objective” environmental uncertainty using different proxies. Some have advocated archival estimates of an environment’s complexity and dynamism (AEU), which are primary determinants of unpredictability (e.g., Dess & Beard, 1984; Downey & Slocum, 1975). Others have espoused *perceived* environmental uncertainty (PEU) as a valid proxy (e.g. Duncan, 1972; Lawrence & Lorsch, 1967). As a proxy, perceived uncertainty ought to be, in theory, highly correlated with archival measures, even though empirical data have not strongly supported this conclusion (e.g., Tosi et al., 1973). Most have attributed the low correlation to perceptive error (Downey et al., 1977)—different actors may perceive uncertainty to be stronger (e.g., anxiety) or weaker (e.g., overconfidence) than it really is. Dess and Beard (1984: 56), Milliken (1987: 135), and others (e.g., Packard & Clark, 2020b) also argue that complexity and dynamism need not imply unpredictability per se. The general consensus, then, is that “AEU and PEU have the same conceptual foundations but are different methodological concepts” and have not been found to be highly correlated only because “the instruments must be operationalized with rather different (inter-)subjective data sources” (Lueg & Borisov, 2014: 661). Under this consensus, entrepreneurial uncertainty has persisted as a single construct.

#### 1.3.1 Representationalism versus the all-seeing eye

Per realism, environmental uncertainty *imposes* upon actors, causing them to alter their behavior. However, representationalism implies a rather different conclusion—that all external phenomena are *fully mediated*

<sup>3</sup> We might put this differently in that the internal/external uncertainty distinction divides the factors that cause uncertainty at the boundary of the skin. But we could just as easily draw that boundary at one’s consciousness, in which case the internal/external distinction would collapse into a single external or “true” uncertainty construct.

by their perception, including what is called environmental uncertainty. This is not merely an admission that we do not always perceive reality as it really is, although that is certainly true (e.g., Aleman & Larøi, 2008; Hoffman & Prakash, 2014; Warren, 1970). More fundamentally, representationalism allows our experiences to be comprised of a vast array of inputs beyond strict sensory impingements. When one experiences a symphony, that experience is much more than the mere perception of a processual sequence of vibrations. It also evokes a subjective or *epistemic* experience, which can include inspiring imagination and arousing emotions. There is a correspondence between the objective and the subjective insofar as reality is (and can be) accurately perceived and mentally represented, but this correspondence is inherently weak—not just because perception is faulty, but more fundamentally because mental representation is an epistemic exercise. One theory of consciousness, for example, posits that “perception [is] a process of inference, so that perceptual content is constituted by the brain’s “best guess” of the (hidden) causes of sensory input” (Seth & Hohwy, 2021: 89). Thus, representationalism rejects the all-seeing eye; the epistemic realm is not fully or even directly tethered to the ontological realm (Packard, 2017, 2018). Thus perception is always and necessarily incomplete (bounded) and often overtly inaccurate (Felin et al., 2017). What *is* and what is *thought* are theoretically distinct.

### 1.3.2 Representationalism and uncertainty

Elaborating this representationalist view further, there can be no “true” (ontological) uncertainty. Uncertainty is a subjective *state of being* (epistemic phenomenon) and not an objective *state of affairs* (ontological reality)—there is no uncertainty until and unless there is one who is uncertain. Representationalism thus implies that the modern concept of uncertainty must be divided and distinguished. The question should not be whether archival or self-report measures are better proxies of a single “true” uncertainty construct, but whether they measure the same thing at all. Whereas its ontological and epistemological dimensions have so far been confounded—the notion of perceived uncertainty reflecting the bounded perception of “true

uncertainty”—representationalism distinguishes these as theoretically and empirically distinct. We note that rejecting the all-seeing eye does not imply a rejection of the ontological dimension altogether; it simply holds that such reality is never observed “objectively,” a feat that would require an all-seeing eye.

AEU in the realist tradition is, for representationalism, not a measure of “uncertainty” at all. Rather, it captures an environment’s *unpredictability*—an objective state of affairs that impinges upon an actor’s perception and, thus, their capacity to foresee some future state of affairs. In contrast, “uncertainty” is a state of mind, a judgment or assessment of the possibility of surprise or error (Shackle, 1953, 1969). Environments, then, cannot be “uncertain” (they have no consciousness) but only “unpredictable.” Because the term “uncertainty” has been widely used to reference both “objective” environmental unpredictabilities and “subjective” conscious uncertainties, we will hereafter use the terms “**objective unpredictability**” and “**subjective uncertainty**” for clarity. While these are, certainly, conceptually related and empirically correlated, they are theoretically and empirically distinct and should not be confounded.

### 1.3.3 Objective unpredictability

Objective unpredictability has been attributed to the complexity (Child, 1972; Duncan, 1972), dynamism or volatility (March & Simon, 1958; Tosi et al., 1973), and munificence (Dess & Beard, 1984) of an environment. Complexity refers to “the level of complex knowledge that understanding the environment requires” (Sharfman & Dean, 1991: 683). Dynamism or volatility reflects the rate of change due to, e.g., innovation and competitive dynamics (Miller & Friesen, 1983). Munificence is “the level of resources available to firms from various sources of the environment” (Tan, 1996: 33), reflecting the level of hostility among resource-dependent competitive firms (Covin & Slevin, 1989).

Yet, as both Knight (1921) and Shackle (1949, 1969) have observed, there is an additional factor that scholars from the strategic management subdiscipline have generally overlooked in connection with environmental uncertainty, one that is especially critical

and consequential for entrepreneurship: *situational novelty*.

The practical difference between the two categories, risk and uncertainty, is that in the former the distribution of the outcome in a group of instances is known (either through calculation a priori or from statistics of past experience), while in the case of uncertainty this is not true, the reason being in general that it is impossible to form a group of instances, because the situation dealt with is in a high degree unique. (Knight, 1921: 223)

Novel situations need not be complex or volatile, and yet such circumstances remain unpredictable for the primary reason that the actor does not yet have the causal knowledge required to deduce next states. Entrepreneurial action is often defined in terms of novel productive action (e.g., Packard, 2017) and thus, in a literal sense, is antithetical to objective predictability.

Thus, with Lachmann (1977: 90) we conclude, that “the impossibility of prediction in economics follows from the facts that economic change is linked to change in knowledge, and future knowledge cannot be gained before its time.” That is, entrepreneurial outcomes are objectively unpredictable in a sense beyond that captured by present AEU metrics.

### 1.3.4 Subjective uncertainty

What has, in the realist tradition, been called *perceived uncertainty*, or PEU, more aptly reflects what we have labeled “subjective uncertainty.” However, whereas PEU is traditionally understood as the perceptual internalization of objective unpredictability, such perception is, for representationalism, only a single antecedent of subjective uncertainty, which is, as Shackle (1949, 1969) explains, a judgment of the possibility of surprise, an admission that future states could be other than expected.

When [one] is certain that a particular answer to some question is right, he means that that answer by itself exactly fills the vacant place constituted by the question, leaving no room for any other suggested answers (Shackle, 1969: 47).

Subjective uncertainty has been attributed or even equated to ignorance (Shubik, 1954), ambiguity (March,

1994), equivocality (Weick, 1979), incommensurability (Spender, 1989), and other “procedural uncertainties” (Dosi & Egidi, 1991) and “knowledge problems” (Townsend et al., 2018). However, it is in fact and ultimately caused by an *awareness* of such limitations. In contrast, a lack of such awareness leads to certainty of expectations, a perception of predictability and a confidence in predictions, even where such confidence might not be justified (Hayward et al., 2006).

## 2 Uncertainty versus unpredictability in entrepreneurial action

If objective unpredictability and subjective uncertainty are conceptually distinct, then theoretical models that employ a single uncertainty concept are incomplete. But to understand how or why they are incomplete, let us dig further into how, precisely, these constructs are distinguishable within the causal chain of events.

### 2.1 Acting with subjective uncertainty

While the future may be unpredictable to varying degrees, the mind can always imagine possible scenarios through mental simulation processes (Barron and Klein, 2016) using constructed mental models of reality (Johnson-Laird, 1983), resulting in the prediction and expectation of possible outcomes given specific inputs, including possible actions (Lachmann, 1976; Shackle, 1969, 1979). Through such imagination, human agents become planners, forecasting the future, anticipating the consequences of future states, making mental and physical preparations for those expected outcomes, and devising action schemes by which they might alter the impending outcomes to their benefit (Lachmann, 1977). Yet, they are limited in their ability to forecast outcomes for reasons of objective unpredictability, and they become aware of their limitations through experience as their predictions fail (Siegenthaler, 1997). This awareness generates subjective uncertainty, which manifests experientially as doubt (Hastie, 2001; McMullen and Shepherd, 2006).

To elaborate this basic intuition, we turn to Shackle’s (1949, 1969) theory of potential surprise. Shackle explains that it is *expectations*—“those originative acts of mind, involving degrees of doubt and belief

assigned to the products of imagination” (Shackle, 1949: ix)—from which decisions are made and a specific action instigated. In Shackle’s framework (as with others, e.g., Kahneman & Tversky, 1982; Savage, 1954), subjective uncertainty plays a primary role in ranking expectations and, from them, determining a preferred action:

The intensity of enjoyment of a given hypothetical outcome by imagining it in advance is no doubt a function of several variables, but two of these are, I think, likely to be dominant; this intensity will plainly be an *increasing* function of the *desirability* of the outcome in question, and a *decreasing* function of the degree of potential surprise associated with it. (Shackle, 1949: 18)

This concept of “potential surprise” warrants some elaboration. While classical uncertainty theorists—Knight,<sup>4</sup> Keynes, Savage, Arrow, Tversky and Kahneman, etc.—almost universally focused their theorizing on *objective unpredictability* (while using the language of “uncertainty”), Shackle’s (1949, 1969) theory is uniquely focused on *subjective uncertainty*:

The state of mind which accompanies a feeling of certainty or a high degree of belief is one of *repose*. A man who is making plans on a basis of working assumptions which he feels to be very doubtful is always, as it were, looking over his shoulder at these assumptions, on the watch for events which would compel him to abandon them; he is on the alert, and the occurrence of such events would not shock him to the same degree as if he had fully accepted his working assumptions. It is only a man who feels very sure of a given outcome who can be greatly *surprised* by its non-occurrence. (Shackle, 1949: 10)

Thus, Shackle posits that subjective uncertainty can be assessed in terms of the degree of surprise one would experience were that outcome to not occur, with higher “potential surprise” corresponding to

lower subjective uncertainty and vice versa. This subjective uncertainty derives from the fact that estimations of possibility are subjective (Savage, 1954; Shackle, 1949). One’s recognition of such subjectivity, and the admission of potential error, promotes subjective uncertainty (Knight, 1921) or lower potential surprise (Shackle, 1969)—they would be less surprised at being wrong. The magnitude of the subjective uncertainty, and the preoccupation that it has upon the mind, hinges upon the magnitude of the possibility of the expected outcome (inversely) as well as the potential consequences of its not occurring for the actor’s plans. A low possibility might be assessed if the actor imagines many other possibilities, if they are aware that they lack understanding of the causal mechanisms at play, or if they recognize the outcome set to be incomplete (Packard et al., 2017; Shackle, 1969). For entrepreneurs, their subjective uncertainty often derives from situational unfamiliarity or perceived novelty, which drives a recognition that the outcome possibilities are likely to be outside of familiar experience.

Where an actor’s subjective uncertainty (potential surprise) is strong for particular option-outcome pairs, such options become less (un)attractive. Thus, subjective uncertainty, concerning certain action options, alters the structure and rank ordering of options such that a different action may become preferred. Subjective uncertainty implies recognition of multiple possible outcomes to a particular action, and so may evoke emotions such as fear, timidity, and anxiety. Actions taken despite high uncertainty are often intended to account for the uncertainty, for example by acting more cautiously or by using intermediate actions (such as insurance policies or hedging) to try to address the unpredictabilities that they perceive. In the entrepreneurial context, where they are more subjectively uncertain, we expect that entrepreneurs will engage in additional uncertainty mitigation or management behaviors, such as business planning, gathering information about competition, prototype testing, and product improvements.

**H1.** Comparatively, subjective uncertainty will have a larger positive effect on uncertainty mitigation and management behaviors than objective unpredictability.

<sup>4</sup> Recently, scholars have reexamined Knight’s work and found it to contain both objective unpredictability and subjective uncertainty (Packard, Bylund, & Clark, 2021). It is his use of the term ‘uncertainty’ for both that has arguably been the source of the endless confusion that we herein attempt to resolve.

We note that, because representationalism assumes that actions originate epistemically, where both variables are modeled together one would expect only the subjective uncertainty variable, and not the objective unpredictability variable, to exhibit a direct effect. In lieu of hypothesizing a null effect for objective unpredictability, which is generally considered bad practice (but see Frick, 1995), we utilize a comparative approach as a practical way to empirically test the theorized mechanisms of representationalism.

### 2.1.1 Actions and outcomes

While subjective representations are directly and fully causally related to actions, the theoretical connection between actions and outcomes is more complicated. Entrepreneurial outcomes depend not only on the entrepreneur's actions but are also contingent upon a host of other variables. Entrepreneurs perform their actions within the flow of time to influence the trajectory of events (Wood et al., 2021) such that the reality that emerges entails a higher value state—for the consumer and, thus, for the entrepreneur—than would otherwise have been attained without those specific actions. Because such actions must occur in the present, their consequences to emerge only at some later time, and because the factors that interact to effect this consequential state of affairs are various and often complex and dynamic (Duncan, 1972), such consequences or outcomes are objectively *unpredictable*. That is, the correspondence between actions and the state of affairs that actually emerges (i.e., “outcomes”) is, except in highly controlled environments (i.e., not entrepreneurship), tenuous due to the multitude of factors that come into play.

The effects of entrepreneurial action depend, to a large extent, on the accuracy of their assumptions regarding the causal factors that correspond to the preferred outcome. In the context of entrepreneurship, success hinges on the entrepreneur's accurate prediction of consumers' future wants (Bylund & Packard, 2022; Packard & Burnham, 2021), and of what will best satisfy those wants. Such entrepreneurial activities are awash with sources of both epistemic (i.e., mitigable) unpredictabilities, such as technological and financial feasibility, and aleatory (i.e., immitigable) unpredictabilities, such as future demand and possible competitive responses (Packard & Clark, 2020a, b).

Efforts to engage in observation, search, measurement, and data processing can provide causal knowledge and information that entrepreneurs can use to mitigate the epistemic unpredictabilities and improve prediction. Thus, entrepreneurs can improve expected performance outcomes by engaging in prediction and planning activities (Chwolka and Raith, 2012) such as researching their prospective markets and potential competition and searching for, collecting, processing, and synthesizing the information required to craft a business plan.

However, in socially complex contexts where large numbers of agents can behave in *ex ante* unpredictable ways, efforts to mitigate aleatory unpredictabilities through predictive planning and data collection may not yield substantial performance benefits (Packard & Clark, 2020b, c). Instead, entrepreneurs may better manage such circumstances via learning and adaptive activities (Sarasvathy, 2001), e.g., prototyping, market testing, and feedback monitoring.

The trade-offs between predictive and adaptive strategic approaches lend to a conclusion that entrepreneurs in contexts of comparatively greater aleatory uncertainties will be predisposed toward and generally benefit from an adaptive approach, while those in more established and stable industries may do better from the efficiencies that prediction affords (Packard & Clark, 2020b). Mobile app development—our empirical context—for example, is a highly innovative and hypercompetitive setting where the primary unpredictabilities include fickle consumer preferences and low-cost competitive response and entry, both aleatory and immitigable (Barlow et al., 2019). In contrast, the epistemic unpredictabilities of the industry—technological and financial feasibility, for example—are comparatively easy to mitigate. Thus, while there is variance in objective unpredictability in the mobile app industry, aleatory unpredictabilities are more-or-less universally stronger than the epistemic unpredictabilities in this context. As a result, predictive actions are expected to be comparatively unproductive. Instead, per effectuation theory (Sarasvathy, 2001), we expect app developers to do better with adaptive-reactive decision strategies to manage the unpredictabilities of fickle consumer preferences and easy competitive entry, and that such adaptive approaches will generally outperform predictive approaches.



More specifically, in accordance with our representationalist framework, we expect that this effect will positively correspond to the relative objective unpredictability of the external environment, and not necessarily to the subjective uncertainties of the entrepreneur.

**H2.** Comparatively, adaptive entrepreneurial actions will have a more positive impact on entrepreneurial performance outcomes when objective unpredictability is high than when subjective uncertainty is high.

In short, representationalism posits that the mechanics of subjective uncertainty are theoretically distinct from those of objective unpredictability in their implied effects on entrepreneurial actions and outcomes. Let us now empirically examine these conclusions.

### 3 Methods

#### 3.1 Data and measures

Our data source is the Google Play app store ([play.google.com/store/apps](http://play.google.com/store/apps)), the official mobile application store for devices running the Android operating system. Using web-scraping techniques, we collected data for all 9993 apps that were listed on Google Play's categorical lists of "top new" apps on June 7, 2015. We continued collecting data longitudinally for this cohort of apps that were published on Google Play each week for one year, ending on June 15, 2016.

This scraped data is supplemented with survey responses from the app developers. We emailed an online survey link to the 9993 app developers on June 10, 2015. Participants were asked a series of questions about their human capital, the actions they took to produce and market the app, and how novel and innovative they perceived their app to be. On average, it took participants 11.5 min to complete the survey. No compensation was offered for participation in the survey. On July 2, 2015, the survey's closing date, 1378 surveys had been started (13.8 percent response rate) and 946 had been finished. However, 101 of these responses were tied to apps that did not have text descriptions written in English on Google Play. These apps were excluded from our sample since we

analyze app text descriptions to create our measure of objective unpredictability. Thus, our final sample consists of 845 unique apps published on, or up to 74 days before, June 7, 2015, with 32,934 app-week observations collected through June 15, 2016.

On average, at the time we first scraped data, the apps included in our sample were more likely to offer in-app purchases (14.0% vs. 11.1%,  $t$ -stat=2.497) or charge a fee to install their app (9.2% vs. 5.3%,  $t$ -stat=4.665), had higher review scores (4.55 stars vs. 4.40 stars,  $t$ -stat=5.467), had fewer logged app downloads (4.04 vs. 4.89,  $t$ -stat=9.112), and were newer (15.1 days old vs. 20.5 days old,  $t$ -stat=3.653) than the apps for which we did not obtain survey responses. Although some response bias is present, we conclude that our sample is valid since it provides us with responses from economically minded, high-quality app developers that had more recently released the focal app that we observed in this study.

#### 4 Objective unpredictability and subjective uncertainty measures

Because unpredictability is multidimensional, we measure objective unpredictability in two different ways: *environmental volatility* and *situational novelty*. First, we follow strategic management scholars who developed archival environmental uncertainty (AEU) measures based on an industry's volatility (Lueg and Borisov, 2014). However, the standard 10-year measure of industry volatility (Tosi et al., 1973) is not plausible for many entrepreneurial endeavors, including our research context of the app store, which does not yet have such an established history. To adapt this traditional metric, then, we created a measure of *objective unpredictability (volatility)* by calculating the range in performance—as gauged by the number of app downloads—for a focal app's ten closest competitors in the Google Play app store. The greater the range in the downloads of these competitor apps, the more unpredictable (i.e., difficult to forecast) the focal app's performance is assumed to be. The creation of this measure is a two-step process.

First, we use text analysis to identify a focal app's ten most similar neighbors (Hoberg & Phillips, 2010). When publishing an app on the Google Play platform, developers must write a text description which can explain, among other things, the features

and benefits of their app. Applying natural language processing techniques, we removed words that do not appear in the English dictionary, removed stop words (e.g., “the,” “your,” “for”), and stemmed words to their root form (e.g., “fish” would be the stem for “fishing,” “fisher,” and “fished”). This leaves us with a word vector for each app that can be compared to the word vectors of other apps using basic cosine similarity (Hoberg & Phillips, 2010; Hoberg et al., 2014; Kwon & Lee, 2003). To elaborate, we calculate the pairwise basic cosine similarity between the focal apps in our sample and all of the other apps in the same Google Play category as of May 2015<sup>5</sup> using the count vectorizer method as shown in formula (1) where  $A$  represents the word vector for a focal app,  $B$  represents the word vector for an app published by a competitor,  $i$  represents each unique word used in the two apps’ descriptions, and  $n$  represents the total number of unique words used in the two apps’ descriptions:

$$\frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}} \quad (1)$$

This allows us to identify the ten closest competitors (i.e., most similar apps published by other developers) for each focal app. Of course, this text-based method is subject to error since text descriptions only capture a portion of the similarity between apps. However, prior work has established that such measures can be used as reliable indicators of between-app similarity (Angus, 2019; Barlow et al., 2019; Piening et al., 2021).

Next, from this list of a focal app’s ten most similar competitors, we identify the range in performance (i.e., downloads). To do this, we subtract the number of downloads for the app from this group of competitors with the lowest number of downloads from the number of downloads for the app with the highest number of downloads. We then log this result to correct for extreme skewness. For example, if the most successful competitive app has 1 million downloads and the least successful competitive app has 1000 downloads, objective unpredictability would be

higher ( $\ln(1,000,000 - 1000) = 13.8$ ) than if the highest competitive performer has 10,000 downloads and the lowest has 1000 ( $\ln(10,000 - 1000) = 9.1$ ). This variable provides a nuanced estimate of how unpredictable performance outcomes might be for a focal app, given the volatility in the performance outcomes among a group of similar—but exogenous—apps. We standardize this logged number to facilitate comparison to our measure of subjective uncertainty.

Our second measure, *objective unpredictability (novelty)*, is constructed in a similar way by subtracting the average similarity score of each focal app compared to its ten nearest neighbors from one (since we are interested in novelty rather than similarity). A score of 0.0 would indicate that the focal app has an identical text description to its ten nearest neighbors and hence, is not at all novel. In contrast, a score approaching 1.0 would indicate that the focal app is highly novel since it shares almost none of the same words with its ten nearest neighbors. This measure aligns with the theory developed above, which emphasizes the role of novelty in objective unpredictability within the entrepreneurial context (Knight, 1921; Shackle, 1969).

Together, these measures capture two primary and distinct causes of entrepreneurial unpredictability. Objective unpredictability (volatility) effectively captures “state” unpredictability, while objective unpredictability (novelty) better captures the “effect” and “response” unpredictabilities of entrepreneurship (cf. Milliken, 1987), because highly novel apps have no similar cases from which to form expectations (Knight, 1921).

*Subjective uncertainty* is estimated using survey measures of perceived novelty and innovativeness. We combine two survey questions to create this measure. The first question is: “You believe that your app is 1 (pretty similar to at least one other app, product, or service) to 7 (completely unlike any other app, product, or service).” The second question is: “Your customers would most likely say that your app is 1 (not at all innovative) to 7 (extremely innovative).” We interpret higher scores for both questions as being suggestive of greater subjective uncertainty driven by the uniqueness and innovativeness of the app. The responses to these questions are reliably correlated, with a Cronbach’s alpha of 0.713. To calculate subjective uncertainty, we standardize the sum of the responses to these two survey questions.

<sup>5</sup> We draw on a larger data set collected separately with 1.15 million apps listed in Google Play in May 2015 when identifying the ten nearest neighbor apps.

#### 4.1 Entrepreneurial action measures

We measure actions, or observable efforts of the developer to achieve a successful outcome in three ways. First, we create a dichotomous measure of whether respondents indicate that a business plan has been formally prepared or at least informally or partially written (1) or remains completely unwritten (0). This action variable measures efforts to engage in predictive, planning actions and is time invariant, obtained via survey response shortly after the app was published.

Second, we measure the number of prototype tests respondents conducted by asking “In total, how many individuals provided feedback on prototype (beta) versions of your app before it was first released? (do NOT count individuals who helped develop the app).” This variable measures an adaptive, flexible action developers can engage in before app publication. Third, we measure at the app-week level, how many times a developer updated its app over the course of our year-long observation period. According to Chen et al. (2021), mobile app developers generally adopt a three-digit versioning system (e.g., 1.0.2). In this versioning system, increments in the first digit represent major changes to the product, including core feature additions or alterations. Increments in the second digit represent comparatively minor changes and increments in the third digit represent bug fixes. We interpret changes to the first digit as the greatest indication of a developer’s willingness to proactively engage in high-effort adaptive actions with the potential to increase performance trajectories after publication. We interpret changes to the second and third digits as adaptive, but more reactionary actions that require a lower degree of effort and which may be associated with a lower likelihood of significantly improving future performance. We therefore capture the count of major (first digit) and minor (second and third digits) app updates separately in our tests of how actions affect performance outcomes.

#### 4.2 Performance outcome measure

We measure performance outcomes by the logged number of downloads each app had received on a weekly basis. Google Play provides downloads data

in a categorical format, with 19 categories of app installs (e.g., 0, 1 to 5, 5 to 10, 10 to 50, ...1 billion to 5 billion). To create this measure, the lowest number in the categorical downloads range is identified, one is added to this number (to correct for cases with zero downloads), and then this number is logged to account for skewness. Importantly, Google Play does not increment the number of downloads an app has received when users merely install version updates.

#### 4.3 Controls

We include a variety of control variables. At the developer level, we control for the development organization’s age, as measured by the number of days since the organization’s first app was published, as well as the number of apps a developer had published prior to the focal app. At the respondent level, we include dummy variables indicating whether the respondent worked alone on the focal app or not and whether the respondent considers herself or himself to be an owner of the development organization. We also control for the respondent’s years of education and number of other startups the respondent had owned or co-owned. At the app level, we control for the number of days the app had been listed on Google Play and the length of the app’s text description (logged to correct for skewness). We also include dummy variables indicating whether the app offered in app purchases, the app cost money to download, and the respondent indicated that it was extremely, very, or somewhat important to get as many downloads as possible for the app. Also included is a measure of how many downloads (logged to correct for skewness) the respondent predicted the app would have after three months. Finally, we include fixed effects for each of Google Play’s 41 app market categories.

## 5 Analysis and results

### 5.1 Analysis

We use a variety of analytical models to test our first hypothesis depending on the nature of the action-dependent variable. For our predictive action model (business plan writing) we use logistic regression

since the dependent variable is dichotomous, keeping only the first observation for each app. For our first adaptive action model, we use Poisson regression to estimate the count of prototype tests respondents performed before the app was published, again keeping only the first observation for each app. For our second adaptive action, app updates, we use Poisson regression to estimate the count of app updates (to any digit) performed during the data collection period, keeping only the last observation for each app.

We also use a variety of models to test our second hypothesis. We use ordinary least squares regression to explore the effects of objective unpredictability and subjective uncertainty on the relationship between the time-invariant pre-publication adaptive action of prototype testing and logged app downloads, (at the time an app was last observed). We split the sample at the means of objective unpredictability (volatility), objective unpredictability (novelty), and subjective uncertainty to facilitate interpretation of the results. Finally, we use fixed effects ordinary least squares regression panel models to account for unobserved, time-invariant app-specific characteristics to examine the effects of objective unpredictability and subjective uncertainty on the relationship between the post-publication adaptive action of app updating and the change in logged app download from 1 week to the next. Since we hold our objective unpredictability and subjective uncertainty measures constant at the time an app was first observed, we must split the sample to explore these effects. All models employ robust standard errors. In no case do VIF scores suggest that multicollinearity is a problem, with mean VIF scores below 3.0.

## 6 Results

Table 1 presents the summary statistics and correlations for the variables included in this study. All of these variables are time invariant, captured at the time each app was last observed. As shown in this table, our standardized subjective uncertainty and objective unpredictability measures are not at all correlated ( $r=0.00$  for our volatility measure of objective unpredictability and  $r=0.04$  for our novelty measure of objective unpredictability), lending empirical support to our baseline arguments in favor of representationist interpretation of the “environmental uncertainty”

construct. For our predictive action variables, 37% of respondents had written a business plan. For our adaptive action variables, an average of 6.26 pre-publication prototype tests were performed and each app received an average of 0.31 major updates and 1.91 minor updates after publication during our year-long observation period. On average, apps had 6.62 logged app downloads (750 raw downloads) when last observed.

The results from our tests of H1 are found in Table 2. Models 1, 3, and 5 are control models. Model 2 tests the comparative effects of subjective uncertainty and objective unpredictability on business plan writing. As theorized, subjective uncertainty has a positive impact ( $\beta=0.284$ ,  $p=0.001$ ) on business planning while neither objective unpredictability measure has a significant effect at the  $p<0.05$  level. Moving from one standard deviation below the mean of subjective uncertainty to one standard deviation above the mean increases the probability that a business plan was written by 33%, from 0.321 (95% C.I. 0.278 to 0.363) to 0.427 (95% C.I. 0.382 to 0.470). This finding lends support to H1.

In model 4, we find that only subjective uncertainty ( $\beta=0.214$ ,  $p=0.000$ ), and not objective unpredictability, is strongly positively related to the adaptive action of the number of prototype tests performed before app publication. In other words, as suggested by H1, it is subjective uncertainty, rather than objective unpredictability (whether measured by volatility or novelty), that is positively associated with prototyping behaviors. Moving from one standard deviation below the mean of subjective unpredictability to one standard deviation above its mean is associated with a 53% increase in the predicted count of prototype tests performed, which rises from 4.833 (95% C.I. 4.203 to 5.462) to 7.410 (95% C.I. 6.674 to 8.145). Thus, we find strong evidence in support of the notion that subjective uncertainty is positively related to the pre-launch adaptive action of prototype testing, predicted by H1. However, in Model 6, neither subjective uncertainty nor objective unpredictability are found to be positively associated with the total number of app updates (both major and minor) a developer makes.

Table 3 shows the effects of pre-launch actions (both predictive and adaptive) on performance outcomes for our testing of H2. Model 1 is the control model. Here we observe that objective

**Table 1** Summary statistics and correlations

Variable	Mean	SD	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) App downloads (logged)	6.62	2.57	0.69	13.82							
(2) Subjective uncertainty	0.00	1.00	-2.09	1.89	-0.04						
(3) Objective unpredictability (volatility)	0.00	1.00	-2.91	3.39	0.19	0.00					
(4) Objective unpredictability (novelty)	0.00	1.00	-3.77	2.50	-0.06	0.04	-0.07				
(5) Business plan	0.37	0.48	0	1	0.13	0.15	0.02	-0.04			
(6) Prototype tests	6.26	8.03	0	30	0.15	0.24	0.04	0.01	0.27		
(7) App updates (major)	0.31	0.90	0	11	0.10	0.03	-0.01	-0.04	0.04	0.04	
(8) App updates (minor)	1.91	3.56	0	26	0.31	0.06	0.08	-0.05	0.08	0.09	0.12
(9) Developer age	523	303	20	2,131	0.01	-0.03	0.02	-0.01	-0.08	0.00	-0.04
(10) Developer apps	4.46	5.02	1	21	0.01	-0.05	-0.05	-0.11	-0.03	-0.16	-0.01
(11) Solo developer	0.48	0.50	0	1	-0.06	-0.09	-0.02	-0.02	-0.29	-0.27	0.00
(12) Owner	0.90	0.30	0	1	0.03	0.02	0.05	-0.04	-0.09	-0.12	0.03
(13) Years of education	15.76	2.45	10	20	0.05	0.08	0.04	-0.06	0.06	0.06	-0.04
(14) Startup experience	1.04	1.81	0	19	-0.04	0.10	-0.02	-0.02	0.22	0.16	0.03
(15) App age	360	80	10	446	0.23	0.00	0.00	0.00	0.00	0.00	0.13
(16) Description length (logged)	5.99	0.85	2.49	7.76	0.24	0.13	0.09	-0.18	0.17	0.19	0.08
(17) In-app purchases	0.16	0.36	0	1	0.26	0.03	0.11	-0.01	0.06	0.07	-0.05
(18) Paid	0.08	0.27	0	1	-0.28	0.05	-0.02	-0.08	-0.11	-0.03	0.03
(19) Downloads forecast (logged)	6.59	2.71	1	16	0.64	0.09	0.21	-0.09	0.21	0.22	0.03
Variable	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(8) App updates (minor)											
(9) Developer age	-0.04										
(10) Developer apps	-0.08	0.40									
(11) Solo developer	-0.04	0.00	-0.02								
(12) Owner	0.00	-0.02	0.02	0.24							
(13) Years of education	0.01	0.05	0.04	-0.13	-0.13						
(14) Startup experience	-0.03	0.02	0.07	-0.12	0.04	0.05					
(15) App age	0.22	0.04	0.00	-0.01	0.00	0.02	-0.01				

**Table 1** (continued)

(16)	Description length (logged)	0.22	0.00	0.01	-0.16	0.01	0.10	0.01	0.01
(17)	In-app purchases	0.17	0.04	-0.03	-0.13	0.03	0.09	0.03	0.01
(18)	Paid	-0.03	-0.02	0.00	0.02	0.07	-0.02	-0.03	0.00
(19)	Downloads forecast (logged)	0.17	0.01	0.06	-0.19	0.03	0.06	0.09	0.00
									0.22
									0.08
									-0.10
									0.25
									-0.14

*N* = 845 apps with survey responses containing complete information. All variable measurements in this table were captured at the time each app was last observed

unpredictability (volatility) has a positive and significant effect on app downloads ( $\beta=0.216$ ,  $p=0.005$ ). Although this seems counterintuitive, recall that this measure of objective unpredictability (i.e., the download variance across a focal app's ten most textually similar competitors) necessarily implies that an app has the highest objective unpredictability where at least one competitor app has received a high number of downloads and at least one competitor app has received a low number of downloads. The presence of a highly successful competitor suggests that there is established market demand for a particular type of app, which could increase the expected performance of a new app, on average. However, the simultaneous presence of low-performing competitors makes it difficult to predict precisely how, on a wide spectrum of competitive performance, the focal app will perform. In contrast, in our data objective unpredictability (volatility) is typically lowest when *all* of a focal app's closest competitors have received very few downloads (it was rare for an app's competitors to be all successful). In other words, there is low unpredictability where the introduction of an app is near all unsuccessful competitors—it is easy to (correctly) predict that the new app will also have low performance. In contrast, Model 1 shows that subjective uncertainty is negatively related to app downloads ( $\beta = -0.288$ ,  $p=0.000$ ).

Table 3, Model 2 introduces the effect of pre-launch actions (i.e., business planning and prototype testing) and finds that only prototype testing produces a positive and significant effect ( $\beta=0.022$ ,  $p=0.022$ ). In models 3 and 4, we explore whether the value of prototype testing (a pre-publication flexible action) is affected by the level of objective unpredictability (volatility), as H2 suggests. Here, we only observe a significant effect for prototype testing in Model 4 where objective unpredictability (volatility) is low (i.e., below the mean) ( $\beta=0.035$ ,  $p=0.003$ ). A different result emerges when using the objective unpredictability (novelty) measure, as in models 5 and 6. As model 5 shows, prototype testing only has a positive effect when objective unpredictability (novelty) is high ( $\beta=0.025$ ,  $p=0.046$ ). As expected, models 6 and 7 indicated that splitting the sample along subjective uncertainty does not affect the utility of this flexible, adaptive action. Based on these results, we conclude that H2 receives support based on our novelty measure of objective unpredictability. Notably, these

**Table 2** Regression models predicting business planning, prototype testing, and app updating actions

Variable	Model 1 Business plan (Logistic)	Model 2 Business plan (Logistic)	Model 3 Prototype tests (Poisson)	Model 4 Prototype tests (Poisson)	Model 5 App updates (Poisson)	Model 6 App updates (Poisson)
Subjective uncertainty		0.284** [0.087]		0.214*** [0.043]		0.018 [0.047]
Objective unpredictability (volatility)		0.009 [0.095]		-0.006 [0.051]		0.082 [0.062]
Objective unpredictability (novelty)		-0.156 [0.095]		0.040 [0.049]		-0.037 [0.058]
Developer age	-0.001** [0.000]	-0.001** [0.000]	0.000* [0.000]	0.000* [0.000]	-0.000 [0.000]	-0.000 [0.000]
Developer apps	0.006 [0.019]	0.005 [0.020]	-0.050*** [0.011]	-0.044*** [0.011]	-0.020 [0.014]	-0.020 [0.014]
Solo developer	-1.129*** [0.180]	-1.128*** [0.182]	-0.514*** [0.098]	-0.476*** [0.096]	0.099 [0.116]	0.103 [0.115]
Owner	-0.342 [0.282]	-0.417 [0.292]	-0.224 [0.115]	-0.254* [0.116]	0.152 [0.143]	0.151 [0.143]
Years of education	0.009 [0.035]	-0.001 [0.035]	0.003 [0.020]	-0.001 [0.020]	-0.023 [0.022]	-0.028 [0.022]
Startup experience	0.262*** [0.061]	0.251*** [0.060]	0.069*** [0.018]	0.061** [0.020]	-0.034 [0.034]	-0.033 [0.033]
App age	-0.006 [0.009]	-0.007 [0.010]	-0.004 [0.004]	-0.002 [0.004]	0.003*** [0.001]	0.003*** [0.001]
Description length, logged	0.296** [0.110]	0.235* [0.110]	0.155** [0.052]	0.139* [0.054]	0.454*** [0.068]	0.433*** [0.071]
In-app purchases	-0.124 [0.262]	-0.180 [0.268]	0.049 [0.105]	0.027 [0.103]	0.587*** [0.126]	0.574*** [0.125]
Paid	-0.574 [0.326]	-0.665* [0.328]	0.026 [0.149]	-0.021 [0.149]	0.051 [0.191]	0.031 [0.194]
Downloads forecast, logged	0.098** [0.034]	0.083* [0.035]	0.079*** [0.016]	0.069*** [0.017]	0.073*** [0.018]	0.067*** [0.018]
Category effects	Included	Included	Included	Included	Included	Included
Constant	-2.381* [1.078]	-1.782 [1.107]	0.602 [0.621]	0.701 [0.631]	-4.255*** [0.799]	-4.015*** [0.825]
App observations	842	842	845	845	845	845
Pseudo-R-squared	0.165	0.176	0.184	0.205	0.189	0.192

Robust standard errors in brackets. \*\*\* $p < 0.001$ , \*\* $p < 0.01$ , \* $p < 0.05$ . Observations are dropped when category effects perfectly predict outcomes in models 1 and 2. These models lend support to H1 by showing that it is subjective uncertainty, not objective unpredictability, that is positively associated with business planning, prototype testing, and app updating actions

**Table 3** Ordinary least squares regressions examining whether objective unpredictability and subjective uncertainty affect the relationship between the pre-launch adaptive action of prototype testing when predicting final app downloads (logged)

Variable	Model 1	Model 2	High Obj. Unp. (volatility) Model 3	Low Obj. Unp. (volatility) Model 4	High Obj. Unp. (novelty) Model 5	Low Obj. Unp. (novelty) Model 6	High Subj. Unc Model 7	Low Subj. Unc Model 8
Business plan		-0.104 [0.148]	-0.017 [0.266]	-0.001 [0.195]	-0.273 [0.201]	0.058 [0.234]	-0.034 [0.229]	-0.110 [0.213]
Prototype tests		0.022* [0.010]	0.007 [0.019]	0.035** [0.012]	0.025* [0.012]	0.023 [0.016]	0.016 [0.011]	0.025 [0.018]
Subjective uncertainty		-0.311*** [0.072]	-0.102 [0.112]	-0.395*** [0.100]	-0.340*** [0.093]	-0.255* [0.117]	-0.754*** [0.177]	-0.352* [0.170]
Objective unpredictability (volatility)		0.216** [0.076]	0.235 [0.255]	0.365* [0.151]	0.157 [0.092]	0.284* [0.129]	0.421*** [0.120]	0.078 [0.098]
Objective unpredictability (novelty)		-0.022 [0.073]	-0.180 [0.137]	0.080 [0.096]	-0.044 [0.176]	-0.084 [0.155]	-0.060 [0.110]	-0.031 [0.103]
Developer age		-0.000 [0.000]	-0.000 [0.000]	-0.000 [0.000]	-0.001* [0.000]	0.000 [0.000]	-0.000 [0.000]	-0.000 [0.000]
Developer apps		0.004 [0.015]	0.006 [0.026]	0.020 [0.020]	0.021 [0.022]	-0.008 [0.022]	-0.013 [0.024]	0.020 [0.019]
Solo developer		0.474** [0.147]	0.632* [0.265]	0.605** [0.204]	0.600** [0.218]	0.438 [0.225]	0.803*** [0.231]	0.352 [0.217]
Owner		-0.028 [0.231]	0.020 [0.457]	-0.115 [0.273]	0.053 [0.320]	-0.069 [0.366]	-0.198 [0.316]	0.195 [0.330]
Years of education		0.024 [0.028]	-0.029 [0.047]	0.055 [0.036]	-0.029 [0.036]	0.076 [0.044]	0.050 [0.043]	-0.010 [0.036]



**Table 3** (continued)

Variable	Model 1	Model 2	High Obj. Unp. (volatility) Model 3	Low Obj. Unp. (volatility) Model 4	High Obj. Unp. (novelty) Model 5	Low Obj. Unp. (novelty) Model 6	High Subj. Unc Model 7	Low Subj. Unc Model 8
Startup experience	-0.077 [0.041]	-0.086* [0.041]	-0.043 [0.079]	-0.105* [0.050]	-0.105 [0.060]	-0.086 [0.056]	-0.139* [0.054]	-0.064 [0.055]
App age	0.003*** [0.001]	0.003*** [0.001]	0.003 [0.001]	0.004*** [0.001]	0.004** [0.001]	0.003 [0.001]	0.003* [0.001]	0.004*** [0.001]
Description length, logged	0.545*** [0.081]	0.529*** [0.081]	0.691*** [0.135]	0.430*** [0.113]	0.477*** [0.113]	0.558*** [0.122]	0.555*** [0.122]	0.522*** [0.119]
In-app purchases	0.659** [0.202]	0.661** [0.202]	0.290 [0.305]	1.018*** [0.286]	0.494 [0.275]	0.800** [0.306]	0.562* [0.272]	0.781** [0.299]
Paid	-2.624*** [0.279]	-2.625*** [0.274]	-3.225*** [0.456]	-2.364*** [0.366]	-2.056*** [0.402]	-3.006*** [0.365]	-2.890*** [0.419]	-2.387*** [0.394]
Downloads forecast, logged	0.463*** [0.037]	0.454*** [0.038]	0.466*** [0.053]	0.443*** [0.052]	0.475*** [0.044]	0.425*** [0.060]	0.449*** [0.045]	0.492*** [0.062]
Category fixed effects	Included	Included	Included	Included	Included	Included	Included	Included
Constant	-1.280 [0.876]	-1.273 [0.860]	-1.199 [1.448]	-1.372 [1.142]	-0.058 [1.173]	-2.555 [1.341]	-1.472 [1.235]	-0.669 [1.201]
Number of apps	845	845	327	518	448	397	403	442
R-squared	0.536	0.540	0.606	0.514	0.574	0.565	0.585	0.570

Robust standard errors in brackets. \*\*\* $p < 0.001$ , \*\* $p < 0.01$ , \* $p < 0.05$ . App downloads (logged) are predicted at the time each app was last observed. Models 3 and 4 are run on subsamples where objective unpredictability (volatility) is above or below zero, respectively. Models 5 and 6 are run on subsamples where objective unpredictability (novelty) is above or below zero, respectively. Models 7 and 8 are run on subsamples where subjective uncertainty is above or below zero, respectively. These models show that business planning is unrelated to app installs while prototype testing is positively related to app installs, particularly when objective unpredictability (volatility) is low and when objective unpredictability (novelty) is high

results suggest that the benefits of prototyping are confined to the unpredictabilities related to novelty, and not to unpredictabilities that result from performance variability. We might infer from this that the benefits of prototyping are in validating unpredictable value, which performance volatility metrics do not clearly capture.

In Table 4, we present the regression models used to test the relationship between app updates and changes in performance, controlling for app and week fixed effects. More specifically, these models explore the effects of making an app update (either major or minor) 1 week on the change in app downloads (logged) the following week. Model 1 shows that major app updates are generally beneficial ( $\beta=0.108$ ,  $p=0.030$ ), as are minor app updates ( $\beta=0.094$ ,  $p=0.000$ ). In models 2 through 7, the effect of minor updates remains positive and significant, but is statistically indistinguishable from the effect size observed in Model 1. In other words, the benefit of minor app updates is not moderated by the level of objective unpredictability or the level of subjective uncertainty in this empirical context.

Model 2 shows that major app updates become significantly more beneficial when objective unpredictability (volatility) is high (greater than 0) ( $\beta$  increases from 0.108 in Model 1 to 0.275 ( $p=0.011$ ) in Model 2). In contrast, when objective unpredictability (volatility) is low (less than or equal to 0), as in Model 3, there is no significant relationship between major app updates and changes in app downloads. Models 4 and 5 explore app updating effects when the sample is split at the mean of objective unpredictability (novelty). Here, major app updates become significantly more beneficial when objective unpredictability (novelty) is low ( $\beta=0.178$ ,  $p=0.031$  in model 5). Our intuition here is that this may be because highly novel apps do not get sufficient market feedback to prompt such updates. We also observe, in model 7, that major app updates are significantly related to performance when subjective uncertainty is low ( $\beta=0.179$ ,  $p=0.031$ ). In an unreported analysis (omitted to conserve space), we find that this effect only holds when objective unpredictability (volatility) is high or when objective unpredictability (novelty) is low, suggesting that it is actually objective unpredictability rather than subjective uncertainty that is driving these results. Overall, these results indicate support for H2,

but only when drawing on our volatility-based measure of objective unpredictability.

### 6.1 Robustness tests

We probe the robustness of these results in a variety of ways. These models are omitted to conserve space but are available upon request from the authors. For H1, we adopt ordered categorical measures for the number of hours respondents spent writing business plans and conducting prototype tests (0 h; 1–25 h; 26–50 h; 51–75 h; 76–100 h; and more than 100 h) and find similar results. We also run the main models separately on the individual survey measures of novelty and uniqueness, again finding similar results. In addition, we run a random effects regression to predict the probability that a developer will update their app in a given week but, as in our main models, do not find a significant relationship between either subjective uncertainty or objective unpredictability and app updating.

For H2's tests of pre-publication actions, we used the ordered categorical hour measures in place of our main measures. In this case, we find that none of the actions, including prototyping hours, are significantly related to app downloads. This suggests that the number of individuals with whom a developer tests prototypes is more important than the amount of time the developer spends conducting these tests. We also run the panel models incorporating random effects, keeping all observations for each app, and finding similar results. For H2's fixed effects tests of post-publication actions, we change the lag between updates and changes in installs to 1 and 2 weeks. Again, these specifications generate results consistent with our main findings.

## 7 Discussion

We propose that there has been a pernicious “all-seeing eye” assumption in entrepreneurship, like the other social science disciplines. In entrepreneurship, however, the significance and impact of this assumption on our science are especially strong due to the theoretical centrality of individual beliefs and actions (McMullen & Shepherd, 2006). Various efforts to unravel the causes of entrepreneurial action (see Parker, 2009, Ch. 4 for a review) have, in this sense,

**Table 4** Ordinary least squares fixed effects panel regressions examining whether objective unpredictability and subjective uncertainty moderate the relationship between the post-launch adaptive action of app updating when predicting the change in app downloads (logged) from week to week

Variable	High Obj. Unp. (volatility)		Low Obj. Unp. (volatility)		High Subj. Unc (novelty)		Low Subj. Unc (novelty)	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	
Count of app updates (major)	0.108* [0.050]	0.275* [0.108]	0.065 [0.050]	0.035 [0.071]	0.178* [0.082]	0.045 [0.073]	0.179* [0.082]	
Count of app updates (minor)	0.094*** [0.017]	0.085** [0.026]	0.103*** [0.020]	0.091*** [0.026]	0.097*** [0.023]	0.094*** [0.019]	0.099** [0.033]	
App fixed effects	Included	Included	Included	Included	Included	Included	Included	
Week fixed effects	Included	Included	Included	Included	Included	Included	Included	
Constant	3.996*** [0.041]	4.473*** [0.071]	3.694*** [0.049]	3.899*** [0.054]	4.108*** [0.061]	3.961*** [0.057]	4.028*** [0.058]	
App-week observations	32,934	12,756	20,178	17,618	15,316	15,802	17,132	
R-squared	0.556	0.559	0.557	0.557	0.559	0.566	0.551	
Number of apps	845	327	518	448	397	403	442	

Robust standard errors in brackets. \*\*\* $p < 0.001$ , \*\* $p < 0.01$ , \* $p < 0.05$ . Models 2 and 3 are run on subsamples where objective unpredictability (volatility) is above or below zero, respectively. Models 4 and 5 are run on subsamples where objective unpredictability (novelty) is above or below zero, respectively. Models 6 and 7 are run on subsamples where subjective uncertainty is above or below zero, respectively. These models show that making major app updates is positively associated with an increase in app installs from week to week, particularly when objective unpredictability (volatility) is high, objective unpredictability (novelty) is low, and subjective uncertainty is low

been perhaps overly deterministic, theoretically bypassing the central and mediating roles of individual intentionality in these causal processes. In fact, prevailing philosophical thought regarding human perception implies that all cognition is composed of representations—we do not perceive reality directly, but “see” only images mentally constructed from sense stimuli.

While we recognize that our fundamental point—that perception is not reality—is widely accepted and intuitively obvious, we also hasten to note that our contribution is far more fundamental and profound than simply pointing out the obvious. If our conclusions are correct (regarding uncertainty specifically) that perception is not reality, then why do we continue to treat them, scientifically, as if they were the same (but with error)? Perception is *not* reality but with error. It is subjectively constructed and at least partially intentional. Further, we argue that they are not merely distinct, but that they occupy distinct theoretical positions within entrepreneurial action theory.

While they are causally connected, they have different causes and effects.

Accepting what may seem obvious on the surface in fact requires a profound shift in the theory and metatheory of our social scientific endeavors. The implications of accepting representationalism are, in fact, severe. It includes a radical rethinking at both the meta-theoretical and theoretical levels. The meta-theoretical implications have been the subject of various efforts to rethink the philosophical underpinnings of our science (e.g. Alvarez et al., 2014; Bylund & Packard, 2022; McBride & Wuebker, 2022; Packard, 2017, 2018; Ramoglou, 2021). Our interest here, however, has been at the abstract-theoretic level, i.e., what does representationalism mean for the basic assumptions and tenets of entrepreneurial action theory. One such theoretical implication is the badly needed theoretical separation of objective unpredictability from subjective uncertainty, as we have herein developed.

In our empirical investigation of app developers, we observed strong evidence that objective

unpredictability is not equivalent to subjective uncertainty, dispelling the long-supposed accuracy of the positivist tradition and its “all-seeing eye” in entrepreneurial research. An environment may be highly unpredictable, but an actor within that environment need not necessarily be subjectively uncertain about it. This result casts strong doubt over classical research on “environmental uncertainty,” i.e., objective unpredictability and its role within the entrepreneurial process (see Magnani & Zucchella, 2018 for a review). Indeed, we did not find subjective uncertainty (which directly influences entrepreneurial action) to be fully or even partially reflected by our measures of objective unpredictability. It is certainly possible, perhaps even common, for entrepreneurs’ uncertainty to correlate only loosely, if at all, with what is truly unpredictable.

In this research, we have focused specifically on the role of uncertainty as a key factor in the entrepreneurial journey depicted by entrepreneurial action theorists (McMullen & Shepherd, 2006; Packard et al., 2017). Uncertainty is indisputably key in the entrepreneurial process, but its role has often been oversimplified through the lens of a presumptive all-seeing eye. That is, we often depict uncertainty as having a direct dampening effect on entrepreneurial action. But this is a clear oversimplification. Uncertainty is a subjective state of mind (McMullen and Shepherd, 2006). Our empirical study strongly validates representationalism’s distinction between an objective state of affairs and our perceptions of and reactions to it. It is one’s *epistemic reality* that drives action (McBride & Wuebker, in press)—empirically, all of our models testing the effect of subjective uncertainty on pre-launch entrepreneurial actions showed a positive relationship. App developers with higher subjective uncertainty were more likely to perform additional pre-publication actions, such as writing a business plan, conducting research on competitors, and prototype testing the app with a larger number of beta testers. Interestingly, subjective uncertainty did not significantly affect app developers’ response to market feedback post-publication, as measured by app updating behaviors. The observed difference in the effects of subjective uncertainty on pre- and post-product launch actions highlights the importance of accounting for time in studies of entrepreneurial action (Rindova & Martins, 2022; Wood et al., 2021) and merits further exploration.

Ontological reality, on the other hand, has less direct say in the actions we perform than commonly understood. Empirically, we found a significant direct relationship between objective unpredictability and only one of the aforementioned entrepreneurial actions: hours spent researching competition. Thus, we observed, generally, that mental representations are the primary driver of pre-publication uncertainty mitigation adaptive and planning entrepreneurial actions. We must take greater care, then, in ensuring this distinction between environmental or situational *unpredictability* and individual *uncertainty* about the environment or situation. They may often be correlated (Lueg & Borisov, 2014), but they are theoretically and empirically distinct.

We also empirically validated recent arguments that, within the context of strong “aleatory” (i.e. immitigable) uncertainty, the *type* of action matters such that adaptive, flexible actions with frequent judgment revisions and course corrections are preferable and more strongly associated with entrepreneurial success than predictive, planning actions (Packard & Clark, 2020a, b, c). In our models, both adaptive actions—pre-publication prototyping and post-publication updates—increased app success. Such activities, of course, come at a cost of streamline efficiency, which is generally preferable in more stable strategic contexts where prediction and planning are more viable. Such planning actions were of no observable consequence in our study, as neither business plan writing nor competitor research drove performance outcomes. Thus, our study finds, in the context of mobile app development, that flexibility and adaptation were critical to success (cf. Sarasvathy, 2008) while planning was not, in line with our theorizing.

However, our results suggest that, at least in the context of app development, prototype testing is generally beneficial, while post-publication updating (in the form of major app feature change updates, rather than simple bug fixing) is particularly beneficial under high objective unpredictability. While the latter is consistent with our theorizing, intuition would suggest that prototyping ought to be comparatively more beneficial under higher unpredictability also. One possibility for this result is that, unlike our measure of app updating, our measure of prototyping is not granular enough to distinguish prototype testing performed to learn and generate substantive feature changes from prototype testing performed simply to

debug the app or to generate pre-publication market interest. Additionally, the benefits of app prototyping are in the feedback from consumers in the usability of an interface and its features. However, research suggests that customers are limited in their ability to provide such feedback because their creativity is constrained by, and to, familiar solutions (Bennett & Cooper, 1981; Leonard & Rayport, 1997). Furthermore, the pool of beta testers may not be a representative subpopulation compared to the broader population of users who actually pay for (or at least download) the launched app, who have a particular need that they are trying to satisfy. Thus, prototype testing can provide beneficial, though imperfect, information to app developers before they publish an app. When unpredictability is high, it may be particularly unclear whether an app's initial feature set will appeal to customer audiences, post-publication. When unpredictability is high, then, post-launch product use feedback (where developers can see how users are using and misusing the app), what users are trying to do, and how well the app is satisfying real needs may become particularly beneficial to app developers. Again, these results emphasize the importance of considering intertemporality in entrepreneurial action research and warrant further exploration.

## 8 Conclusion

Entrepreneurs are a rare breed, not because they are different in nature but because they see something different, they *want* something different, and entrepreneurship is understood by them to be the best means to those distinct ends. Perception and intention belong center-stage in a theory of entrepreneurship (Bird, 1988; Fayolle & Liñán, 2014). To put them there may require rethinking the foundations of our science (Berglund, 2015; Packard, 2017). This research is an effort to empirically show how and why such a shift is warranted and clarifies one of the most common and consequential assumptions in social science. Uncertainty and unpredictability are distinct and should be theoretically and empirically distinct. Let us reject the all-seeing eye and renew our efforts to study entrepreneurship through the eyes of entrepreneurs themselves.

## References

- Aleman, A., & Larøi, F. (2008). *Hallucinations: The science of idiosyncratic perception*. American Psychological Association.
- Alvarez, S. A., Barney, J. B., McBride, R., & Wuebker, R. (2014). Realism in the Study of Entrepreneurship. *Academy of Management Review*, 39(2), 227–231.
- Anderson, C. R., & Paine, F. T. (1975). Managerial perceptions and strategic behavior. *Academy of Management Journal*, 18(4), 811–823.
- Angus, R. W. (2019). Problemistic search distance and entrepreneurial performance. *Strategic Management Journal*, 40(12), 2011–2023.
- Ariely, D. (2008). *Predictably irrational: The hidden forces that shape our decisions*. HarperCollins.
- Azzouni, J. (2017). *Ontology without borders*. Oxford University Press.
- Barlow, M. A., Verhaal, J. C., & Angus, R. W. (2019). Optimal distinctiveness, strategic categorization, and product market entry on the Google Play app platform. *Strategic Management Journal*, 40(8), 1219–1242.
- Barron, A. B., & Klein, C. (2016). What insects can tell us about the origins of consciousness. *Proceedings of the National Academy of Sciences*, 113(18), 4900–4908.
- Baum, J. R., Locke, E. A., & Smith, K. G. (2001). A multi-dimensional model of venture growth. *Academy of Management Journal*, 44(2), 292–303.
- Bennett, R. C., & Cooper, R. G. (1981). The misuse of marketing: An American tragedy. *Business Horizons*, 24(6), 51–61.
- Berglund, H. (2015). Between cognition and discourse: Phenomenology and the study of entrepreneurship. *International Journal of Entrepreneurial Behavior & Research*, 21(3), 472–488.
- Bird, B. (1988). Implementing entrepreneurial ideas: The case for intention. *Academy of Management Review*, 13(3), 442–453.
- Buchko, A. A. (1994). Conceptualization and measurement of environmental uncertainty: An assessment of the Miles and Snow perceived environmental uncertainty scale. *Academy of Management Journal*, 37(2), 410–425.
- Bylund, P. L., & Packard, M. D. (2022). Subjective value in entrepreneurship. *Small Business Economics*, 58, 1243–1360.
- Chalmers, D. J. (2004). The representational character of experience. In B. Leiter (Ed.), *The Future for Philosophy* (pp. 153–181). Clarendon Press.
- Chater, N., Felin, T., Funder, D. C., Gigerenzer, G., Koenderink, J. J., Krueger, J. I., Noble, D., Nordli, S. A., Oakford, M., & Schwartz, B. (2018). Mind, rationality, and cognition: An interdisciplinary debate. *Psychonomic Bulletin & Review*, 25(2), 793–826.
- Chen, L., Wang, M., Cui, L., & Li, S. (2021). Experience base, strategy-by-doing and new product performance. *Strategic Management Journal*, 42(7), 1378–1398.
- Chia, R. (1996). The problem of reflexivity in organizational research: Towards a postmodern science of organization. *Organization*, 3(1), 31–59.

- Child, J. (1972). Organizational structure, environment and performance: The role of strategic choice. *Sociology*, 6(1), 1–22.
- Chwolka, A., & Raith, M. G. (2012). The value of business planning before start-up—A decision-theoretical perspective. *Journal of Business Venturing*, 27(3), 385–399.
- Covin, J. G., & Slevin, D. P. (1989). Strategic management of small firms in hostile and benign environments. *Strategic Management Journal*, 10(1), 75–87.
- Cyert, R. M., & DeGroot, M. H. (1987). *Bayesian analysis and uncertainty in economic theory*. Rowman & Littlefield.
- Dess, G. G., & Beard, D. W. (1984). Dimensions of organizational task environments. *Administrative Science Quarterly*, 29(1), 52–73.
- Dosi, G., & Egidi, M. (1991). Substantive and procedural uncertainty. *Journal of Evolutionary Economics*, 1(2), 145–168.
- Downey, H. K., & Slocum, J. W. (1975). Uncertainty: Measures, research, and sources of variation. *Academy of Management Journal*, 18(3), 562–578.
- Downey, H. K., Hellriegel, D., & Slocum, J. W. (1977). Individual characteristics as sources of perceived uncertainty variability. *Human Relations*, 30(2), 161–174.
- Duncan, R. B. (1972). Characteristics of organizational environments and perceived environmental uncertainty. *Administrative Science Quarterly*, 17(3), 313–327.
- Fayolle, A., & Liñán, F. (2014). The future of research on entrepreneurial intentions. *Journal of Business Research*, 67(5), 663–666.
- Felin, T., Koenderink, J., & Krueger, J. I. (2017). Rationality, perception, and the all-seeing eye. *Psychonomic Bulletin & Review*, 24(4), 1040–1059.
- Fodor, J. A. (1981). Imagistic representation. In N. Block (Ed.), *Imagery* (pp. 63–86). MIT Press.
- Freel, M. S. (2005). Perceived environmental uncertainty and innovation in small firms. *Small Business Economics*, 25(1), 49–64.
- Frick, R. W. (1995). Accepting the null hypothesis. *Memory & Cognition*, 23(1), 132–138.
- Hastie, R. (2001). Problems for judgment and decision making. *Annual Review of Psychology*, 52(1), 653–683.
- Hayward, M. L., Shepherd, D. A., & Griffin, D. (2006). A hubris theory of entrepreneurship. *Management Science*, 52(2), 160–172.
- Hoberg, G., & Phillips, G. (2010). Product market synergies and competition in mergers and acquisitions: A text-based analysis. *The Review of Financial Studies*, 23(10), 3773–3811.
- Hoberg, G., Phillips, G., & Prabhala, N. (2014). Product market threats, payouts, and financial flexibility. *The Journal of Finance*, 69(1), 293–324.
- Hoffman, D. D. (2000). *Visual intelligence: How we create what we see*. WW Norton & Company.
- Hoffman, D. D., & Prakash, C. (2014). Objects of consciousness. *Frontiers in Psychology*, 5(1), 1–22.
- Howell, W. C., & Burnett, S. A. (1978). Uncertainty measurement: A cognitive taxonomy. *Organizational Behavior and Human Performance*, 22(1), 45–68.
- Johnson-Laird, P. N. (1983). *Mental models: Towards a cognitive science of language, inference, and consciousness*. Harvard University Press.
- Kahneman, D. (2011). *Thinking, fast and slow*. Farrar, Straus and Giroux.
- Kahneman, D., & Tversky, A. (1982). Variants of uncertainty. *Cognition*, 11(2), 143–157.
- Knight, F. H. (1921). *Risk, uncertainty and profit*. Hart, Schaffner, and Marx.
- Koenderink, J. (2014). The all seeing eye? *Perception*, 43, 1–6.
- Kolb, F. C., & Braun, J. (1995). Blindsight in normal observers. *Nature*, 377(6547), 336–338.
- Kreiser, P., & Marino, L. (2002). Analyzing the historical development of the environmental uncertainty construct. *Management Decision*, 40(9), 895–905.
- Kwon, O.-W., & Lee, J.-H. (2003). Text categorization based on k-nearest neighbor approach for web site classification. *Information Processing & Management*, 39(1), 25–44.
- Lachmann, L. M. (1976). From mises to shackle: An essay on Austrian economics and the kaleidic society. *Journal of Economic Literature*, 14(1), 54–62.
- Lachmann, L. M. (1977). *Capital, expectations, and the market process: Essays on the theory of the market economy*. Sheed Andrews and McMeel Inc.
- Lawrence, P. R., & Lorsch, J. W. (1967). *Organization and environment: Managing differentiation and integration*. Harvard University.
- Leonard, D., & Rayport, J. F. (1997). Spark innovation through empathic design. *Harvard Business Review*, 75, 102–115.
- Liao, J., & Gartner, W. B. (2006). The effects of pre-venture plan timing and perceived environmental uncertainty on the persistence of emerging firms. *Small Business Economics*, 27(1), 23–40.
- Lorenzi, P., Sims, H. P., & Slocum, J. W. (1981). Perceived environmental uncertainty: An individual or environmental attribute? *Journal of Management*, 7(2), 27–41.
- Lueg, R., & Borisov, B. G. (2014). Archival or perceived measures of environmental uncertainty? Conceptualization and new empirical evidence. *European Management Journal*, 32(4), 658–671.
- Magnani, G., & Zucchella, A. (2018). Uncertainty in entrepreneurship and management studies: A systematic literature review. *International Journal of Business and Management*, 13(3), 98.
- March, J. G. (1994). *Primer on decision making: How decisions happen*. Free Press.
- March, J. G., & Simon, H. A. (1958). *Organizations*. Wiley.
- McBride, R., & Packard, M. D. (2021). On the ontology of action: Actors are not ‘abstractions.’ *Academy of Management Review*, 46(1), 211–214.
- McBride, R., & Wuebker, R. (2022). Social objectivity and entrepreneurial opportunities. *Academy of Management Review*, 47(1), 75–92.
- McKelvie, A., Haynie, J. M., & Gustavsson, V. (2011). Unpacking the uncertainty construct: Implications for entrepreneurial action. *Journal of Business Venturing*, 26(3), 273–292.
- McMullen, J. S., & Shepherd, D. A. (2006). Entrepreneurial action and the role of uncertainty in the theory of the entrepreneur. *Academy of Management Review*, 31(1), 132–152.
- Miller, J. I. (2012). The mortality problem of learning and mimetic practice in emerging industries: Dying to be

- legitimate. *Strategic Entrepreneurship Journal*, 6(1), 59–88.
- Miller, D., & Friesen, P. H. (1983). Strategy-making and environment: The third link. *Strategic Management Journal*, 4(3), 221–235.
- Milliken, F. J. (1987). Three types of perceived uncertainty about the environment: State, effect, and response uncertainty. *Academy of Management Review*, 12(1), 133–143.
- Mises, L. V. (1998). *Human action: A treatise on economics*. Auburn, AL: Ludwig von Mises Institute.
- Packard, M. D. (2017). Where did interpretivism go in the theory of entrepreneurship? *Journal of Business Venturing*, 32(5), 536–549.
- Packard, M. D. (2018). Why I am not a performativist (yet). *Journal of Business Venturing Insights*, 9, 39–44.
- Packard, M. D., & Burnham, T. A. (2021). Do we understand each other? Toward a simulated empathy theory for entrepreneurship. *Journal of Business Venturing*, 36(1), 106076.
- Packard, M. D., & Bylund, P. L. (2021). From *homo economicus* to *homo agens*: Toward a subjective rationality for entrepreneurship. *Journal of Business Venturing*, 36(6), 1–15.
- Packard, M. D., & Clark, B. B. (2020a). Mitigating versus managing epistemic and aleatory uncertainty. *Academy of Management Review*, 45(4), 872–876.
- Packard, M. D., & Clark, B. B. (2020b). On the mitigability of uncertainty and the choice between predictive and non-predictive strategy. *Academy of Management Review*, 45(4), 766–786.
- Packard, M. D., & Clark, B. B. (2020c). Probability logic fails in inmitigable uncertainty, but strategic logic does not. *Academy of Management Review*, 45(3), 704–707.
- Packard, M. D., Clark, B. B., & Klein, P. G. (2017). Uncertainty types and transitions in the entrepreneurial process. *Organization Science*, 28(5), 840–856.
- Packard, M. D., Bylund, P. L., & Clark, B. B. (2021). Keynes and Knight on uncertainty: Peas in a pod or chalk and cheese? *Cambridge Journal of Economics*, 45(5), 1099–1125.
- Parker, S. C. (2009). *The economics of entrepreneurship*. Cambridge University Press.
- Pfeffer, J., & Salancik, G. (1978). *The external control of organizations: A resource dependence perspective*. Harper and Row.
- Piening, E. P., Thies, F., Wessel, M., & Benlian, A. (2021). Searching for success—entrepreneurs’ responses to crowdfunding failure. *Entrepreneurship Theory and Practice*, 45(3), 626–657.
- Ramoglou, S. (2021). Knowable opportunities in an unknowable future? On the epistemological paradoxes of entrepreneurship theory. *Journal of Business Venturing*, 36(2), 106090.
- Reinach, A. (1982). On the theory of the negative judgment. In B. Smith (Ed.), *Parts and Moments: Studies in Logic and Formal Ontology* (pp. 315–378). Philosophia Verlag.
- Rindova, V. P., & Martins, L. L. (2022). Futurescapes: Imagination and temporal reorganization in the design of strategic narratives. *Strategic Organization*, 20(1), 200–224.
- Sarasvathy, S. D. (2001). Causation and effectuation: Toward a theoretical shift from economic inevitability to entrepreneurial contingency. *Academy of Management Review*, 26(2), 243–263.
- Sarasvathy, S. D. (2008). *Effectuation: Elements of entrepreneurial expertise*. Edward Elgar Publishing.
- Savage, L. J. (1954). *Foundations of statistics*. Wiley.
- Seth, A. K., & Hohwy, J. (2021). Predictive processing as an empirical theory for consciousness science. *Cognitive Neuroscience*, 12(2), 89–90.
- Shackle, G. L. S. (1949). *Expectation in economics*. University Press.
- Shackle, G. L. S. (1953). The logic of surprise. *Economica*, 20(78), 112–117.
- Shackle, G. L. S. (1969). *Decision, order, and time in human affairs* (2nd ed.). Cambridge University Press.
- Shackle, G. L. S. (1979). *Imagination and the nature of choice*. Edinburgh University Press.
- Sharfman, M. P., & Dean, J. W. (1991). Conceptualizing and measuring the organizational environment: A multidimensional approach. *Journal of Management*, 17(4), 681–700.
- Shubik, M. (1954). Information, risk, ignorance, and indeterminacy. *The Quarterly Journal of Economics*, 68(4), 629–640.
- Siegenthaler, H. (1997). Learning and its rationality in a context of fundamental uncertainty. *Journal of Institutional and Theoretical Economics*, 153(4), 748–761.
- Simons, D. J., & Chabris, C. F. (1999). Gorillas in our midst: Sustained inattention blindness for dynamic events. *Perception*, 28(9), 1059–1074.
- Snyder, N. H., & Glueck, W. F. (1982). Can environmental volatility be measured objectively? *Academy of Management Journal*, 25(1), 185–192.
- Spender, J.-C. (1989). *Industry recipes*. Basil Blackwell.
- Tan, J. (1996). Regulatory environment and strategic orientations in a transitional economy: A study of Chinese private enterprise. *Entrepreneurship Theory and Practice*, 21(1), 31–46.
- Tosi, H., Aldag, R., & Storey, R. (1973). On the measurement of the environment: An assessment of the Lawrence and Lorsch environmental uncertainty subscale. *Administrative Science Quarterly*, 18(1), 27–36.
- Townsend, D. M., Hunt, R. A., McMullen, J. S., & Sarasvathy, S. D. (2018). Uncertainty, knowledge problems, and entrepreneurial action. *Academy of Management Annals*, 12(2), 659–687.
- Tushman, M. L., & Nadler, D. A. (1978). Information processing as an integrating concept in organizational design. *Academy of Management Review*, 3(3), 613–624.
- Warren, R. M. (1970). Perceptual restoration of missing speech sounds. *Science*, 167(3917), 392–393.
- Weick, K. E. (1979). *The social psychology of organizing*. Addison-Wesley.
- Wood, M., Bakker, R., & Fisher, G. (2021). Back to the future: A time-calibrated theory of entrepreneurial action. *Academy of Management Review*, 46(1), 147–171.