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Entertainment Product Decisions, Episode 4: How to Develop New Successful Entertainment Products

> "Innovation (n). The introduction of something new. A new idea, method, or device."
>
> —Merriam-webster.com/dictionary/innovation

Our discussion in Part I of this book about the short life cycles of entertainment products made a strong case that continuous innovation is critical for firms in this industry. At the same time, the unique characteristics of entertainment products demand approaches to innovation that address these particularities, such as consumers' holistic judgment of (hedonic) entertainment products and the critical role of artists and creatives for the development of new entertainment content. These characteristics are behind the industry's traditional skepticism regarding systematic approaches toward the management of innovation in entertainment, an attitude well in line with the industry's "Nobody-Knows-Anything" mantra.

In contrast to such industry skepticism, we are convinced that entertainment innovations can indeed be managed systematically and quite powerfully. Just look at the track record of animation producer Pixar, whose films have been a remarkable string of successes. The firm's first 18 full-length releases have generated more than $13.2 billion globally in theaters alone (in 2017 value), with an average of more than $700 million per film, and not a single one of their films has made less than $300 million just in ticket sales.

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We find it hard to believe that such stream of successes could be attributed to mere luck—particularly when considering that 12 of the 18 films were *not* based on an existing brand, beyond the firm itself. And we are not the only ones who think so; Pixar has become a role model for innovation management within and even beyond film and entertainment (e.g., Catmull 2008). The firm's innovation skills were a main reason why Disney paid more than $7 billion for Pixar in 2006—and indeed, through sharing personnel and creative resources, Disney has been able to revitalize its own animation division, which has crafted a string of recent hits on their own, including as Frozen and Zootopia (Lussier 2016). Remember that *Entertainment Science* is all about managing the probability of success, and the way Pixar handles innovations obviously influences this probability.

For innovation to occur, there is always a continuum between how much the innovating firm relies on collaboration among a team and, at the other extreme, on individual creatives. The relative importance of collaboration and individuals varies over the innovation process, but also across the different forms of entertainment. Whereas movies and games put more weight on collaboration because of the mere scale and scope of the projects (i.e., bringing a full-blown video game or blockbuster film to market), the individual takes on a somewhat greater weight in the creation of books and music. But even for the latter forms of entertainment, creating a new product is almost always a long process along which those in charge must get numerous ideas right, and collaboration plays an important role.

In any case, we agree with Pixar's Ed Catmull (2008, p. 4) that for creating great entertainment, creativity "must be present at every level of every artistic and technical part of the organization." In what follows, we will take a look at issues at different levels to examine how entertainment firms can be successful through innovation. At the strategic level, we ask what the right environment looks like, what level of innovativeness works best, and whether firms should engage in innovation themselves ("doing it in-house") or partner with others. At the cultural level, we look for values that support effective innovation processes. And at the organizational level, we investigate the people and the structures that are required to make innovation happen.

We complement this firm-level discussion with a detailed look at what *Entertainment Science* can tell us about product-level innovation decisions, with a particular focus on managers' ability to accurately forecast the success of new entertainment projects at different points of the innovation process, a challenge to which *Entertainment Science* scholars have dedicated substantial effort. We will show that systematic forecasting approaches can be powerful alternatives to "Nobody-Knows-Anything" thinking when testing early product concepts and also when optimizing those concepts in later production stages.

The Strategic Dimension of Entertainment Innovations

"I don't make pictures just to make money. I make money to make more pictures."
—Walt Disney *(quoted in IMDb 2017)*

If innovation is the creation of something new, and entertainment product firms need a continuous supply of new products, then managers of entertainment firms need a systematic innovation management process that coordinates the planning, implementation and control of innovation-related actions—to ensure that meaningful innovations continue in a sustainable flow. Even among non-entertainment firms, there is huge variation in the ways innovation activities are handled.

A strategic approach toward new products builds on the distinction between creativity and innovation—whereas the former describes coming up with novel ideas, the latter means the process of actually *implementing* a creative idea and turning it into something marketable (see Amabile 1996). Unless supported by a wealthy benefactor (or the ultra-rare venture capitalist who expects no return on investment), entertainment firms, like any other businesses, are required to generate net positive revenues. Being creative is nice, but the firm will not make money without turning that creativity into commercially successful innovations.

Regarding the strategic dimension of innovation management, an entertainment firm must make decisions regarding three fundamental issues: (1) its innovation goals, (2) the aspired degree of innovativeness of the new products, and (3) its own role in the innovation process (versus the role of other companies). Let's take a look at the options entertainment managers can chose from for each of these issues.

Artistic Versus Economic Innovation Goals

For sustainable innovation management, managers always have to find a balance between the goals they are trying to achieve with new products (usually a combination of economic and artistic goals), the cost of innovation associ-

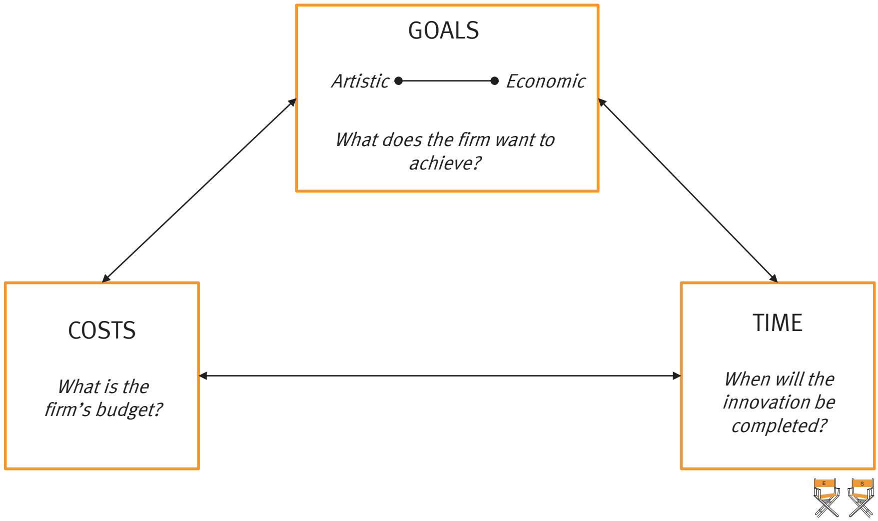

Fig. 10.1 Strategic innovation management requires balancing between three strategic considerations
Note: Authors' own illustration.

ated with reaching those goals, and the time it requires to develop the innovation (see Fig. 10.1).

Although cost and time are widely applicable to entertainment,[253] the desired goals are where we confront the intricacies of entertainment. Economic goals and artistic goals are usually both aimed for by entertainment companies (although not necessarily by the same people in the firm), but they oftentimes clash—something that can be linked to our earlier discussion of taste differences between mass consumers and cultural experts. So before focusing on the "nuts-and-bolts" of how to manage entertainment innovations successfully, entertainment managers first have to determine how to weigh economic and artistic goals.

The tension between artistic and economic goals is inherent for creative products, and it is not difficult to note examples of this clash in firms that produce movies, books, music, and video games. Some entertainment producers aim to avoid this tension by clearly favoring one goal over the other. For example, Israeli cousins Menahem Golan and Yoram Globus, when establishing their Cannon Films in the late 1970s, clearly emphasized economic

[253]Let us note that with regard to the timing dimension of innovation, some particularities also exist for entertainment—we discuss them in our chapter on distribution decisions.

goals. Their business model was to produce low-budget exploitation films for which quality did not matter, or was even a hindrance, according to their argument that "[i]f you make an American film with a beginning, a middle and an end, with a budget of less than five million dollars [the equivalent of about $15 million today], you must be an idiot to lose money" (quoted in Slifkin 2014). But in entertainment, such an approach carries some problems, which eventually led to Cannon's demise—we return to their sad, but instructive story a little later.

Other firms have instead emphasized the artistic aspects. For example, the founding of United Artists was rooted in the belief that innovation decisions in entertainment should be made by the creative artists themselves (see Kehr 2008, Thomson 2008). The firm was founded by four Hollywood heavyweights in 1919: director D.W. Griffith and actors Charles "Charlie" Chaplin, Douglas Fairbanks, and Mary Pickford, who built a distribution company for their own productions, independent of other commercial interests. However, although the creatives had ambitious artistic goals and also experienced strong initial success, their company faced harsh economic realities and volatile profitability when radical artistic visions produced at high costs flopped heavily.

A key event was the collapse of the film Heaven's Gate by high-profile director Michael Cimino. It suffered from the combination of escalated costs ($44 million in production costs alone), terrible reviews, and a bad reception by the viewing public (just $3.5 million in domestic box office). Heaven's Gate ended up as a main contributor to the demise of the United Artists studio (Barber 2015)—it did not help that the film is today held in high esteem by many experts and audiences, including one of this book's authors. Further evidence that having a creative in the driver's seat of an entertainment company is far from a guarantee for long-term success is the story of DreamWorks. The movie studio, co-founded in 1994 and led by acclaimed director Steven Spielberg to enable talented filmmakers to pursue "their more personal projects" (Russell 2004, p. 233), "struggled for financing—and for hits—for much of its existence" (Masters 2016).

Between the extremes of being fully driven by either economic goals or artistic goals, a continuum exists. Our review suggests that some of the most successful entertainment companies have fleshed out an approach near the center of the continuum, fusing artistic ambitions with economic considerations. The reason is that although artistic goals are crucial for creating powerful entertainment products, the opportunities for the artist to *continue* creating new products will be limited without business discipline. Similarly, a focus on business without honoring the relevance of artistic creativity is also doomed in a field where consumers are, at least to a certain extent, driven by creative inspirations. Thus, the uneasy symbiosis between the two kinds of goals should be accepted and managed.

Brad Bird, a director *and* producer at highly innovative *and* successful Pixar, praises this coalescence of commercial and artistic ambitions. He paraphrases Walt Disney's statement we quoted at the beginning of this section, stating that he wants his films "to make money, but money is just fuel for the rocket. What I really want to do is to go somewhere. I don't want to just collect more fuel." Because most, if not all artists will share Mr. Bird's motivation, "making money can't be the focus … for imagination-based companies to succeed in the long run" (quoted in Rao et al. 2008).

Firms that effectively balance artistic and economic goals employ approaches that usually entail the close cooperation of creatives and business managers (e.g., directors and producers), rather than a hierarchy in which one "class" rules over the other. Ed Catmull, Pixar's president, argued that without an understanding of economic realities, resource demands by creatives can be almost unlimited as people can always justify spending more money and time in order to "make a better movie" (Catmull 2008). And while creatives generally understand that money and time are not unlimited, they often do not fully appreciate the costs of various processes. Pixar addresses this via a "Popsicle" approach: starting with a number of Popsicle sticks that represents their total capacity (one stick is a "person-week"—what a typical creative could normally accomplish within a week), creatives and managers work together to allocate the sticks across the elements of the production process (e.g., a certain character in a film). Then, when creatives later ask for additional time and/or more money to devote to one element, the creatives and managers work together to identify other elements from which an equivalent number of sticks can be taken away—in order to stay on time and on budget.

When used in such a way, Catmull and Wallace (2014) argue that budget constraints can be actually facilitating creative processes, as they make people think differently and come up with creative solutions.[254] But they clarify that they can also hurt the work of creatives massively if used differently: when managers of the "Disney Oversight Group," in the mid-2000s, gave the economic goals stark priority and micromanaged even the smallest

[254]Think of the wonderful animated travel map in Raiders of the Lost Ark—which the film's director Steven Spielberg invented "[t]o save money" (*Total Film* 2006).

aspects of production, they impeded the innovation process by robbing creatives of their required freedom.

In sum, the entertainment industry provides examples that both the economic approach and the artistic approach can work for a certain period if done right, but such unbalanced approaches are unstable and tend to collapse at a certain point. In contrast, a purposefully chosen balance between artistic freedom and the careful management of resource constraints (among managers *and* creatives) can be a key to success.

The "Right" Degree of Innovativeness

A second strategic question is: how innovative should an entertainment firm's new products be? According to the sensations-familiarity framework, consumers love familiarity, but can also become satiated by it; at the same time, they love sensations, but only when those sensations trigger the "right" emotions and images. This demand perspective can be matched with a "supply perspective": whereas artists love to indulge their creativity, their radical creations can create new sensations that, even if great pieces of art, are too demanding and radical for consumers to fully appreciate. Meanwhile, managers may crimp the style of artists by preferring to invest in less radical (and more familiar) projects. Thus, the "how innovative?" question is somewhat linked to the prior strategic question about artistic and economic goals.

Innovation research has framed the "degree of innovativeness" challenge as one of *exploitation* versus *exploration*—the former concept describes making use of existing assets when creating new products, whereas the latter refers to the pursuing of new ideas and intellectual properties (March 1991). We have previously shown that the management of entertainment brands, as a case of exploitation, at least at certain points in their life cycle, requires the infusion of new creations, a kind of exploration. But a bigger question is how to optimally manage the brands a producer owns: it deals with the allocation of an entertainment firm's resources *in general*.

So, what does the theory of exploration-exploitation tell us about the "ideal" level of innovativeness? We can learn from it that over-reliance on exploitation can reduce the firm's ability to discover entirely new opportunities, leaving it trapped at a "suboptimal equilibria" (March 1991, p. 71), and can make the firm vulnerable if the market environment changes in ways such that the existing assets (which have been effective for earlier products) become obsolete or less attractive (Greve 2007). Exploitation in entertainment essentially means to use existing brands and products and to focus on extensions within existing categories and with existing brands.

Whereas our discussion above has shown that this can mitigate a variety of risks and be a viable strategy for entertainment companies on a product level, a starkly exploitative strategy, if practiced on the company level, can be a dangerous strategy for an entertainment firm in the longer run for two reasons. First, in the words of John Lasseter, "[s]equels are financially less risky. But if that's all we did, we would become creatively bankrupt" (as Chief Creative Officer for Pixar's and Disney's animation studios; quoted in Franklin-Wallis 2015). What he means is that an over-reliance on entertainment product extensions (not necessarily only sequels, but also other kinds of low-innovative new products) would have an adverse effect on a firm's creatives, who suffer mightily from producing too much of the same content. The departure of the best talent would set off a negative creativity spiral, further reducing a firm's ability to offer sensations to consumers.

The second argument against an "exploitation-only" approach in entertainment is linked to consumers' reactions: because of the satiation embedded in entertainment products and brands, the firms' assets will eventually lose value over time. We have discussed ways to mitigate such value reduction in our brand management chapter, but in the longer run, even the best brand management skills cannot fully counter the satiation inherent in all entertainment and the negative effects it has on revenues. Consumers will eventually grow tired of consuming the "same old, same old." Besides, this is what we observe these days at the entertainment-industry level where exploitation has become the norm—a tendency we consider a threat to the industry as a whole.

In contrast, exploration-based innovations are more likely to be radical, using technologies or pursuing markets that are new to the firm. Innovations of these types are high-risk/high-return: they can produce spectacular market breakthroughs, but because of the high levels of uncertainty involved in exploration-based innovation (de Ven et al. 1999), firms with too heavy reliance on exploration run the risk of incurring the high costs of constant exploration without gaining sufficient net benefits. What United Artists and also DreamWorks did might fall into this category—pointing at the systematic nature of the firms' economic evolution.

Organizations scholar James March (1991) and others conclude that it is wise to try for a delicate balance between the two types of innovation in order to reap the benefits of each while avoiding the traps. Consistent with such scholarly insights, Mr. Catmull has decided that his firm will produce both original films and sequels. "[Originals] are high-risk ideas. So in order to take the high risks, which is very important to us, then we do things which are lower risk. We have to make sure we're also smart as a business."

Let us note, however, that balancing is not trivial from an organizational perspective. The problem with doing so is that the two types of innovation are not easily compatible, because "the mindsets and organizational routines needed for exploration are radically different from those needed for exploitation" (Gupta et al. 2006, p. 695). Exploitation requires tight control around current strategy and current organizational practices—whereas exploration instead eschews tight control and cannot emerge without greater emphasis on discovery (Dougherty and Heller 1994). So, how can the unbalanceable be balanced nevertheless?

Innovation scholars have pointed to two potential paths forward to address this challenge—we illustrate them in Fig. 10.2. One option (shown in Panel A of the figure) is to do both exploration and exploitation at the same time. Doing so has been labeled "ambidexterity," drawing on the analogy of a person who can perform tasks with either hand (Gupta et al. 2006). As successful innovations emerge from the frequent experiments in the firm's exploration unit, those products can be passed along to the exploitation unit for ongoing success. The exploitation unit has a useful supply of new ideas without being distracted by constant experimentation and failures.

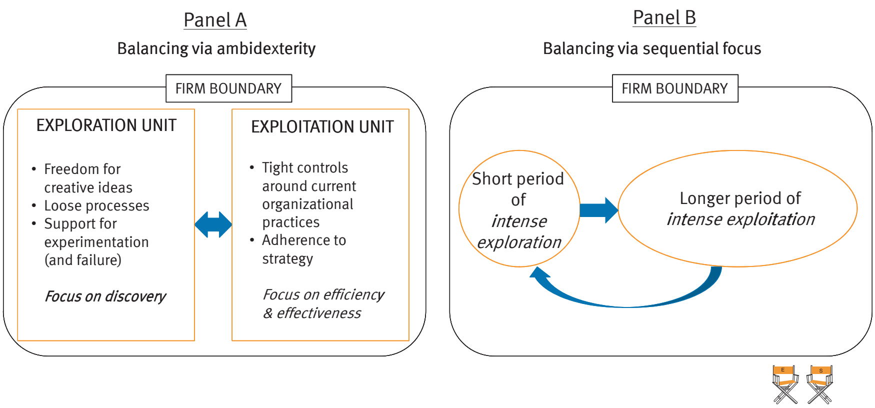

Fig. 10.2 Balancing exploration and exploitation via ambidexterity and sequential focus
Note: Authors' own illustration.

For this approach to work, it is important that the tightly controlled processes that are necessary in the exploitation unit not be allowed to infect the culture of discovery in the exploration unit (Benner and Tushman 2003). Ambidexterity tends to work best when the work of the two cooperating units can be done independently of *other* units (meaning that the firm is large enough to support multiple autonomous units). Disney has acted in line with the ambidexterity approach to innovation on a company level by having kept the originals-focused Pixar a distinct division after purchasing it in 2006, instead of merging it with either Disney Animation (which are put in charge for exploitations of Pixar brands beyond sequels, such as PLANES to CARS) or Disney Studios (which are focusing on exploitation by systematically remaking Disney's original brands such as THE JUNGLE BOOK).[255]

The other option (which we illustrate in Panel B of the figure) is for a firm to switch its attention from one focus to the other at different points in time (i.e., decoupling across time or sequential focus, Gupta et al. 2006). Under this model a firm engages in short periods of intense exploration to create a slate of new innovations. At some point, the firm then shifts to a longer period of exploitation in which those new innovations are fully refined and leveraged in the marketplace. The firm can repeatedly iterate through these stages, over time. If the firm in question is essentially one large system that cannot be easily subdivided into autonomous units, then "sequential attention to exploitation and exploration" is required (Gupta et al. 2006, p. 698).

This is what happens at Disney at the Pixar level: the firm aims for this balance by targeting about two original films for every sequel they produce. With risk-and-return expectations being different between exploitations (i.e., sequels) and explorations (i.e., originals), this balancing approach also resembles ideas we presented in our discussion of managing risk at the slate level, where we concluded that it is important for a firm to balance the risk and returns to their offerings.

In sum, innovation leaders must manage high-wire acts, balancing familiarity against sensations for the consumer's experience and, along with that, balancing risk and freedom for the firm and its artistic creatives. They have to decide about the appropriate ratio of exploration and exploitation to employ in their production slate—and how to accomplish that balance. Our arguments, inspired by innovation theory, have shown that the decision is consequential, as it impacts the attitude of creatives, the responses of consumers, and the risk profile of a firm's slate of innovations.

[255]Other reasons, such as culture, also contributed to this decision—we will get back to them.

Make, Cooperate, or Buy?

A third strategic issue that entertainment firms face when developing innovations is deciding upon the degree to which these innovations are built solely with in-house capabilities—or with assets or capabilities purchased from other firms in the market. This issue is the entertainment version of the classic "make-or-buy" dilemma that economists have wrestled with since the seminal works of Nobel Prize recipients Coase (1937), Arrow (1962), and Williamson (1985). Their foundational works take a "transaction costs" approach that advocates for governing an activity in a way that most efficiently deals with uncertainty and the risk incurred because of that uncertainty (e.g., Walker and Weber 1984). A main insight of the theory is that uncertainty and risks of cooperation require firms to safeguard their interests, which implies the need to evaluate the "relative … merits and demerits of make-or-buy options" (Kurokawa 1997, p. 124). When transaction costs are too high, it is better to "make" the output yourself, but when these costs are lower, a "buy" approach (i.e., cooperation with a partner) would be advantageous.

Early research on transaction costs economics focused on more traditional manufacturing firms, but since then extensive work has found support for the basic tenets of this theory in information technology (e.g., Poppo and Zenger 1998) and high-technology R&D applications (e.g., Kurokawa 1997)—both applications that are somewhat more akin to entertainment innovation. In practice, entertainment innovations are produced across the entire gamut of "make-or-buy" options—let's take a quick look at each option in theory and practice, applying *Entertainment Science* thinking to identify their pros and cons for entertainment product innovations.

The "make" option. The first alternative, and the one often preferred by artists, is to innovate internally, doing everything—from raw idea to finished product—using internal resources. The advantages of such a "making" approach include having complete creative and managerial control over the innovation. The firm's innovation capabilities are improved as each innovation fosters learning, and the firm retains full control of any new intellectual property created for further exploitation. (Be reminded that learning advantages can only be realized in a culture that sees value in such learning—but not in one that honors the "Nobody-Knows-Anything" mantra.)[256] However, there are downsides too—they include "owning" all technological and market

[256]Please see our link between learning and the Goldman mantra in our introduction to this book.

risks in production, while requiring significant investments of time and managerial bandwidth when the innovation is created.

Pixar has always been a distinct proponent of the maker approach, having never bought scripts or ideas from others. "All of our stories, worlds, and characters were created internally by our community of artists" (Catmull 2008). For the firm, the learning that comes from exploring new things on your own has been a main reason: "in making these films, we have continued to push the technological boundaries of computer animation, securing dozens of patents in the process." In the world of video games, Andy Gavin and Jason Rubin, the founders of games producer Naughty Dog, have worked together creating original material since they were 12-year olds. Now leading a team of strong creatives and technical whizzes, Naughty Dog, being part of Sony Interactive Entertainment since 2001, has internally created very successful franchises for the PlayStation console, including The Last of Us and Uncharted (Moriarty 2013).

The "buy" option. The second alternative is to buy innovations that have already been produced by others. For example, Amazon, Netflix and other distributors, in addition to their own creative endeavors and licensing activities, often buy property rights to promising movies at (or even before) film festivals and markets. For example, Amazon paid $10 million for Manchester By The Sea at the 2016 Sundance (Ingram 2017). When Vivendi-owned Studiocanal bought Michael and Rainer Kölmel's Kinowelt, a major reason was Kinowelt's back catalogue of several thousand film titles (Kirschbaum and Hopewell 2008). And in the video game world, Microsoft acquired Minecraft, one of the best-selling games to date with over 120 million copies sold as of 2017, when taking over Mojang, the Swedish indie-game developer that created it (Jones 2014).

An upside of acquisitions is that the quality of a finished product tends to be easier to evaluate and, thus, customer appeal and commercial success can be forecasted more reliably.[257] And there is a potential advantage regarding costs, too—by buying a completed product, the firm foregoes the uncertainty and investments of time and managerial effort that would be required to make innovations (for example, Heaven's Gate eventually consumed three-times its scheduled production costs of around $10 million in 1980—a major contributor to United Artists' troubles). However, a major disadvantage of the "buy" option is that other potential suitors can spot high quality innovations, too, and the increased competition

[257]We discuss the role of timing for success predictions later in this chapter.

can drive costs up considerably, while reducing the likelihood of winning a desired property—something that can be observed today at all major festivals.

Further, depending upon the deal, the seller may impose restrictions on further exploitation of the property by the buyer. And, if the movie or game is acquired as an essentially "finished" product, the buyer may not have the ability to make desired tweaks to content or appearance, along with his or her own company brand image. Finally, an over-reliance on buying finished products may cause the buyer's own in-house innovation capabilities to stagnate, as creatives spend their time polishing up someone else's artistic creation (while potentially browsing for other, more stimulating, employment opportunities).

And finally: *the "cooperate" option*. Innovations usually do not come solely from "100% make" or "100% buy"; firms can make some innovations (or elements of an innovation) and buy others. Further, just as manufacturing firms can enter joint ventures and other alliances, entertainment firms can co-develop innovations with outsiders. This is the traditional Hollywood approach in which a deal on an idea is made before it has gone into production. The studio then partners with the producer (and often also various distributors) to make and market a new film. And the new players in entertainment also act this way. For example, Netflix bought Martin Scorsese's Irish Man, complete with a deal to star Robert De Niro, before it went into production (McNary 2017). The pros and cons of this cooperating option are, just like the strategy itself, a blend of those for make and buy. The buyer gives up some creative and managerial control and accepts more dependence on (the ideally skillful) outsiders. The buying firm might also have to share revenues in the end, depending on the kind of cooperation deal, but it shares risks and, more importantly, gains access to creative content, unique capabilities, and talents that it otherwise would not have.

In sum, it is readily apparent that these three options are not "all-or-nothing" alternatives. Larger firms can combine make with buy actions in their portfolio of projects; whereas Microsoft's use of the Minecraft game was a clear case of "buy," it also purchased the right to "make" extensions of the game on its own, which it has done since the acquisition. In a similar way, film studios often blend their own projects with movies made by others that they buy at festivals and markets. It is critical to examine the relative tradeoffs that come with each solution in light of the entertainment firm's goals, from both a transactional as well as a portfolio perspective.

Some Threats to Systematic Innovation Management in Entertainment

Although some successful entertainment companies have adopted a strategic approach to innovation management, there are threats that can impede the long-term implementation of strategic innovation in entertainment. Figure 10.3 names four such threats—pieces of cheese that can bait entertainment managers into the "innovation mousetrap," if you will. We discuss them next.

The "Artistic Temptation" Threat

A temptation entertainment managers are confronted with is a growing desire to be affiliated with, and respected by, shining artists and stars. When managerial vanity gets paired with a craving for prestige, a manager's economic goals can become overwritten by the artistic value system, reconfiguring the firm's strategic goals. The firm begins to strive for the Oscars (or for just being part of the "star system"), regardless of financial implications.

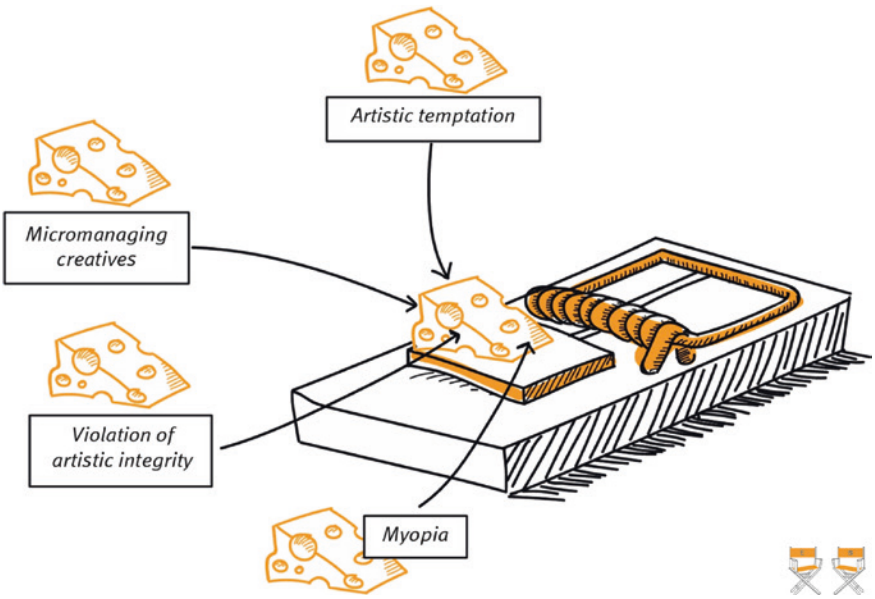

Fig. 10.3 Four threats to systematic innovation in entertainment
Note: Authors' own illustration, design by Studio Tense.

This temptation mostly plays out in smaller ways, but history shows that it can be big enough to bring down a whole firm. Let's take a closer look at the downfall of Cannon Films. As we mentioned earlier, the firm's original business model was to produce low-cost, high-action films with low-to-zero artistic ambitions. However, after having experienced enormous success with that model for a number of years with films such as Missing in Action, Hercules, and American Ninja (and their numerous sequels), the firm's founders became increasingly "eager for prestige" by the mid-1980s (Howe 2013). They no longer wanted to sit at the side table, but to be invited to the big parties, together with the cultural icons of the time.

To achieve this, they dumped their "$5-million-max!" business model for pursuing deals with prominent directors (e.g., Martin Scorsese) and big-name actors such as Dustin Hoffman and Al Pacino, offering some of the biggest paychecks ever seen at that point in time; they also purchased iconic character brands such as Superman and Spider-Man (Pond 1986).

When Cannon paid Sylvester Stallone a then-unprecedented $12 million for his Rocky-like role in the arm-wrestling drama Over the Top ("This time he's fighting with his bare hands," the trailer touted), Mr. Golan and Mr. Globus' craving for *artistic* appreciation was clearly a major motive, and it was not by accident that Mr. Golan put himself in the director's chair for the film. In their quest for awards and respect, the studio also produced radical projects by cultural elitists Jean-Luc Godard, John Cassavetes, and Norman Mailer. The studio lost a lot of money on both their high-budgeted projects and on their "artistic" projects. Figure 10.4 contrasts some of Cannon's initial films with productions after its executives had begun to go for artistic recognition instead on money.

In the end, it was the artistic temptation which led the Israeli cousins astray from their formula—to lose everything (Howe 2013). But the fate of Cannon is certainly not the only case where the artistic dimension of entertainment has influenced business decisions. For example, Comcast CEO Brian Roberts only recently stated that working with director Steven Spielberg has more to offer for him than movies: "It's such an interesting life he lives. How can you not want to be in business with him?" (Masters 2016).

As one film producer told us, the involvement of artists and creatives, along with the products' popularity among consumers and cultural experts, makes the entertainment industry a "vanity business, an emotional business." For effectively managing innovations in such an environment, resisting the artistic temptation threat is a "must" for entertainment managers.

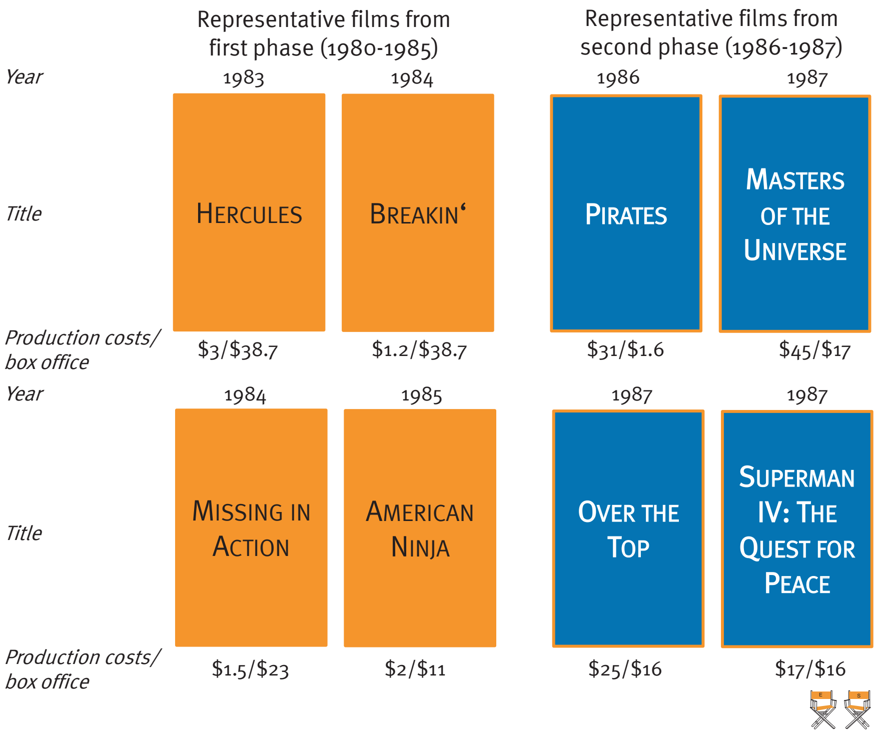

Fig. 10.4 The transformation of Cannon Films
Notes: Authors' own illustration. Box office and production budget data are based on The Numbers and other sources; all numbers are estimates only and not adjusted for inflation. Titles are trademarked.

The "Micromanaging of Creatives" Threat

The "micromanaging" threat is nearly the mirror image of what we just discussed. Whereas artistic temptation can make managers lose sound business judgment, it can also become a serious problem when an entertainment manager treats the creative organization just like any other firm, failing to recognize the unique challenges that are associated with managing creatives in pursuit of business goals.[258] Although we understand the temptation to tightly control the behaviors of artists, whose value systems differ from those of the manager him- or herself, translating business goals into a tight micromanagement of

[258]We outlined these challenges when discussing the "art-for-art's-sake" property of entertainment earlier in the book.

creatives can have the exact opposite effect on the efficiency and effectiveness of the artists' work. In fact, micromanaging creatives can pose a threat not only for art, but also for business.

For movies, we have already mentioned the example of the well-intentioned "Disney Oversight Group." Designed to encourage effective and efficient use of resources, this group actually halted progress on key projects as part of questioning "everything." The results ended up being detrimental to the quality of products and tended to drive away good creative people (Catmull and Wallace 2014). This observation is in line with single-case evidence from the video game industry compiled by scholars Hotho and Champion (2011). Using a case study approach, they collected data over a period of eight months from a small computer games development studio (around 20 artists, developers, and coders) during a time the studio was strategically shifting from doing work-for-hire (small and fast projects for others) to the creation of their own intellectual properties (i.e., two games that were self-funded).

In interviews, the scholars learned that early after the transition, all parties seemed to understand that innovation and creativity were quintessential for the new endeavor, and everyone worked diligently to establish a corresponding goal and value system. However, after mixed initial results (in terms of quality and timeliness), the climate changed—now the artistic "vision" became controlled from the top, and risk-taking was neither encouraged nor present, but replaced by strict plans that led to a downfall in artist autonomy. As motivation and commitment of the creatives waned, creativity evaporated as well. In other words, the attempt to stimulate creativity by controlling it actually led to the opposite, with some employees desiring to return to work-for-hire. In the end, the company announced a reduction in workforce and less emphasis on new intellectual property work.

The "(Perceived) Violation of Artistic Integrity" Threat

But threats to systematic innovation success do not come only from managers (who can either fall in love with artistic goals or launch ill-fated attempts to micromanage artists), but also from artists. All artists value their artistic integrity, but some tend to overemphasize it to a degree that makes it difficult (or even impossible) to fit into a system that simultaneously pursues legitimate business goals.

A well-established explanation of human motivation is self-determination theory (e.g., Deci and Ryan 2000). It states that "intrinsic" motivation—a person's inner drive to perform, a type of motivation that is closely linked to creative performance—is determined by three primary factors: personal autonomy, control, and relatedness. Whereas the relative importance of these drivers varies between people, artists usually value their autonomy most highly. Thus, if an artist feels his or her autonomy is threatened, whether through restrictions on the artist's behavior (or work habits) or by giving final decision making to a manager (and, thus, threatening the "integrity of the art"), his or her motivation can be damaged.

This is crucial, because the performance of creatives and artists is driven by such intrinsic motivation much more so than for other people. Artists typically do things because of an inner impetus rather than for extrinsic stimuli, such as money (which serves more as "validation for creative skills"; Peltoniemi 2015, p. 48). Thus, violating artistic integrity can threaten an otherwise-promising innovation project. Let us stress that it doesn't really matter whether the artist's feeling that his or her autonomy is under siege is objectively true—the mere *impression* that his or her autonomy will be crimped is sufficient for producing these detrimental effects on motivation.

Take the example of young directors Aharon Keshales and Navot Papushado, who had gotten their "dream job" and a "legendary salary" when they were hired for a remake of the 1974 hit movie Death Wish (Fleming 2016). The artists went through stressful interviews with the presidents of MGM and Paramount, as well as being personally approved by star Bruce Willis. A big part of their excitement came from their artistic vision to revive the spirit of the source novel, moving away from the vigilantism-celebrating previous film adaptation; they imagined a thriller in the range of "Taxi Driver, Falling Down…with a bloodcurdling finale like Sicario." However, Keshales and Paushado felt that they could not realize what they had envisioned due to a tight time table and "creative differences." They left the project, despite the fact that this film would have been their entry ticket to Hollywood.

Other artists have shown a similar unwillingness to compromise, perceiving their artistic integrity to be threatened by *any* deviation from their vision. For example, rapper Kanye West stated in an interview: "I do not negotiate. I can collaborate. But I'm an artist, so as soon as you negotiate, you're being compromised" (Bailey 2016). Managers can influence the artist's autonomy perception, but in such radical cases, it might be impossible to integrate an artist into a system in which artistic freedom is balanced with economic considerations.

The "Myopia" Threat

Finally, success itself can be dangerous, threatening systematic innovation. Anyone who is successful with a certain business model or activity is tempted to keep doing what he or she is good at and focusing on staying ahead of the current competition. Successful people become myopic, ignoring the broader framing in which they operate. The danger is that continuity can only work as long as the environment is stable—but once the environment changes, myopia-caused continuity will only lead to failure.

Catmull and Wallace (2014) describe early tech companies in Silicon Valley that got successful fast, attracted lots of smart people, but then failed due to clearly observable and avoidable error. They were myopic—they focused on continuing what made them successful in the first place, paying external attention only to what their direct competition was doing, but without any self-reflection or broader view.

Entertainment firms have fallen prey to a myopia threat in the past. When significant social, political, economic, and technical upheavals were changing society in the late 1960s and early 1970s, Hollywood did not link them to their business model, believing that the changes would not affect movie going. The studios made the same movies they had made for decades, but audiences did not want to see them anymore—myopia brought the "old Hollywood" to the brink of bankruptcy. Finally the financial duress forced the studios and their managers to look outward, resulting in a period of radical transformation that has been called the Hollywood Renaissance, or "New Hollywood" (Kokonis 2009).

More recently, Faughnder (2017) overviewed the high level of turnover among executives within entertainment firms, arguing that the "legacy movie business is under siege" from emerging digital platforms and mobile technologies that have emerged from outside of entertainment firms.[259] As these technologies, which have also disrupted book publishing, the music industry, and reshaped video gaming, gradually alter consumers' entertainment consumption habits, firms must not continue to do what they currently do and only do it "better"; fundamental environmental changes require firms to change their fundamental business models.[260]

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[259]See also our analysis of the entertainment industry's value chain today in our chapter on entertainment business models.

[260]See also Smith and Telang's (2016) detailed analysis of how digitalization is transforming the entertainment business.

So, how can the myopia threat be countered? The key to avoiding such myopia is *self-awareness*—knowing the skills you have, but also what is happening around you, and being open to adapt your business accordingly. These things are closely tied to an entertainment company's culture, which also affects the other threats to innovation we mentioned in this section. So let us take a closer look at the role that culture plays for managing innovation successfully.

The Cultural Dimension of Entertainment Innovation

Strategy is important for powerful innovation, but won't live up to its potential if a firm does not have an innovation-friendly culture. A regular series of breakthroughs will happen only when strategic considerations take place in the "right" culture (and in the "right" organization, but that comes later). For understanding the role of culture for innovation success, a good place to start is to actually clarify what "culture" is. Deshpande et al.'s (1993, p. 24) definition of culture as "the pattern of shared values and beliefs that help individuals understand organizational functioning and thus provide them with the norms for behavior in the organization" is not only consistent with the colloquial meaning of culture as "the way things are around here," but it also stresses the essential role of (shared) values for culture. And it explains why values are so important—because it is those values that drive the behaviors that we observe of a culture.

Organizations vary in the values, beliefs, and norms that comprise their cultures. Likewise, cultures vary in the degree to which they help organizations accomplish their goals—or hinder them (Cameron and Freeman 1991). Whereas a mechanistic culture that features competitiveness, top-down control, and regulations might help to accomplish a clearly defined sales goal, such a culture will likely *not* create the context for the most creative innovations. As Archer and Walczyzk (2006, p. 16) phrase it: "the mechanism that inspires creative people to come up with the perfect design is hardly the same as the one that inspires a salesperson to make a big sale." Research has stressed that in high-creativity environments such as entertainment, effective organizational cultures are those which help to unleash the (typically high) intrinsic motivation of employees, whereas cultures that celebrate the tight management of employees do not work.

More specifically, we have identified four common cultural elements, or "themes," whose presence can contribute to entertainment innovation: (1) the combination of high autonomy and responsibility, (2) the adherence to a shared core goal, (3) an entrepreneurial orientation, and (4) a peer culture built on candor and trust. Their absence, in turn, can inhibit creativity. Our arguments combine scholarly findings with insights from Netflix and Pixar—two firms that have established themselves as highly innovative (and successful) performers in the entertainment industry by stressing the role of a strong culture that facilitates innovation. Let's take a look at the four themes one by one.

Theme 1: Autonomy *and* Responsibility

We have already highlighted that the intrinsic motivation that drives creatives implies a strong emphasis on their ability to act autonomously, thus cultures that celebrate such autonomy should in general facilitate entertainment innovation. But things are somewhat more complicated. Netflix's Reed Hastings (2009) notes something important when he stresses that providing room for autonomy is not the same as the absence of accountability. Instead, he argues that autonomy in entertainment only works for those who also accept the responsibility it carries for the organization. He argues that autonomy and responsibility must be considered as two sides of a coin to stimulate powerful innovation: "Responsible people thrive on freedom and are worthy of freedom."

Figure 10.5 shows combinations of autonomy and the acceptance of personal responsibility as part of a culture. A mechanistic culture that solely focuses on responsibility while not offering freedom to act will cripple creativity, draining the life (and intrinsic motivation) from creatives (lower-right box of the figure). Skipping the responsibility does not improve things; it just enhances passivity and stagnation (lower-left box). What about a culture that stresses autonomy, but does not require accepting responsibility for one's actions? It might have a tendency toward anarchy and chaos (upper-left box). But when both values co-exist, innovation will tend to thrive (upper-right box). So control is not a bad thing per se, particularly when it refers to the outcome of an activity (rather than the process). Taken at face value, to be supportive of innovation, the people who are responsible for quality (i.e., those doing the innovation work) must be empowered to make decisions without having to wait for approval.

An entertainment firm that marries autonomy with responsibility is Guerrilla Games, an Amsterdam-based first-party video games developer

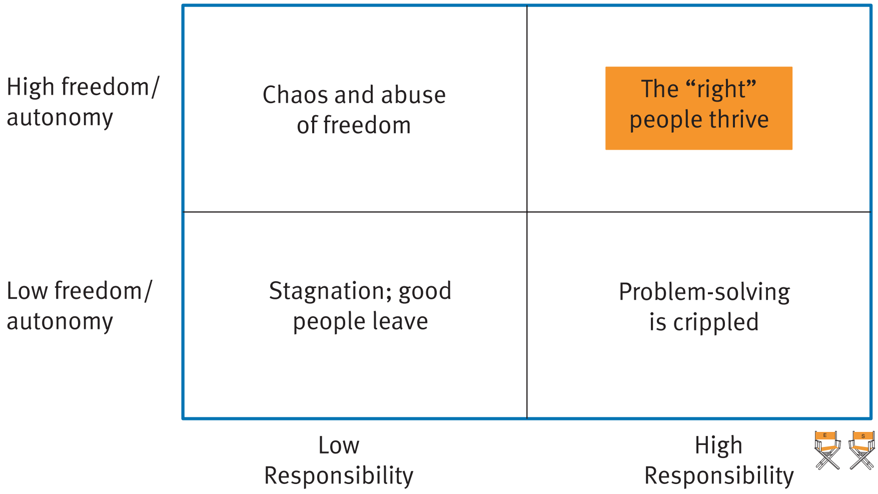

Fig. 10.5 Autonomy must be accompanied by responsibility
Note: Authors' own illustration.

that is owned by Sony Interactive Entertainment since 2005. The firm has successfully launched some of the biggest game innovations for the PlayStation console, such as Horizon Zero Dawn. Managing director Hermen Hulst describes the enormous freedom given to their firm by Sony and to creative employees within Guerilla quite bluntly: “We can do what we want.” However, this freedom comes with conditions: “So far all games at Guerrilla have been profitable. As long as we hold that, we keep our creative freedom” (*AT5* 2017).

A similar balance between freedom and responsibility has been reported for Amazon's film division. According to Christoph Schneider, president of the firm's German business, Amazon considers “creative/artistic freedom .. a fundamental condition for the creation of extraordinary and unique series” (quoted in Kloo 2016). “We at Amazon believe in an idea and a team, which we let work freely. We'll get the cook in the kitchen and just let him cook.… [W]e won't tell him: Hey, you shouldn't use sweet potatoes. As the expression goes, too many cooks spoil the broth” (quoted in Schillat 2017). But he adds that the firm also has performance expectations for new content, which are, like everything else at Amazon, measured via success metrics such as the number of people who have watched the series, how many episodes have been streamed, and if the series is able to attract new customers to Amazon. So the creatives have artistic freedom in the development of a series without interference from management, but the creatives also have to accept responsibility for the market performance of their series.

Theme 2: Adherence to a Shared Core Goal

Scholarly research has compiled strong evidence about the importance of shared goals within an innovation culture (e.g., Gilson and Shalley 2004). For Pixar, the one shared core goal is "excellence." The firm is very reluctant to compromise on quality, prioritizing a great story over anything else (including technology). For example, what we know today as the beautiful Toy Story 2 film was initially planned as a much less ambitious direct-to-DVD release, following demands from then-Pixar partner Disney. But Pixar's executives noted that the lower quality and compromises were destroying morale among employees and decided to aim for the highest ambitions possible instead, creating a theater-worthy premium product.

By doing so, Pixar not only solidified the Toy Story franchise, but learned an important lesson about the motivational benefits of having a relentless focus on quality. According to Pixar's Brad Bird, "If you have low morale, for every $1 you spend, you get about 25 cents of value. If you have high morale, for every $1 you spend, you get about $3 of value. Companies should pay much more attention to morale" (Rao et al. 2008).

Please note that we are not arguing that "highest quality" must be the shared goal of every entertainment company. Instead, our point is that *some* important goal consistent with the firm's values and resource constraints must be shared among the team members to energize coordinated efforts throughout the firm. There can be different shared goals in different entertainment firms, consistent with our discussion in the prior section on the strategic dimension of entertainment innovation. Remember that Cannon was very successful as long as they stuck to their shared goal of making highly profitable exploitation films. A lot of artistic *and* financial failures in entertainment result from the lack of a shared vision among those involved. Take the fifth Dirty Harry film, The Dead Pool, for example: whereas it was certainly not director-star Clint Eastwood's interest to ruin the franchise, the film suffered from the lack of shared goals among those involved. Mr. Eastwood himself later acknowledged that he simply did not know where to take the character anymore when making the film (Brunsdale 2010, p. 362). He agreed to make it in exchange for Warner's support of his own personal ventures (such as the jazz movie Bird).

So, whatever the self-chosen core goal, adherence to and impassioned pursuit of it should be cultivated as a central part of the entertainment firm's culture.

Theme 3: Entrepreneurial Orientation

Innovative cultures benefit from what has been called by scholars an "entrepreneurial orientation": the welcoming of proactivity, a desire for learning (including from failure), an openness to new ideas and experimentation, and a high tolerance for risk (e.g., Lumpkin and Dess 1996). Such an orientation has been found to have a particularly high positive impact on firms' performance in contexts where dynamic market conditions and rapid changes are common. With this being an apt description of entertainment, with its constant need of new ideas and creations and now also the challenging impact of digital technologies, we expect entrepreneurial orientation to immensely benefit entertainment firms also.

The role of failure and how to treat it in a firm's set of shared values deserves special attention. We find it important to note that embracing failure as part of acting entrepreneurial must not be equated with a passive acceptance of it. Only when a person or a firm *learns from failure* does failure become valuable, providing progress towards the accomplishment of a goal. Thus, an entrepreneurial orientation implies that failure must be, especially during the ideation process at the beginning of an entertainment project, regarded as a learning process, and when this the case, people should be encouraged to fail fast and often. However, Pixar's Ed Catmull argues that failure must not be accepted, with people moving on without reflection: "The better, more subtle interpretation is that failure is a manifestation of learning and exploration. If you aren't experiencing failure, then you are making a far worse mistake: You are being drive[n] by the desire to avoid it" (quoted in Clarkson 2016).

Related is the question of what to do with someone who fails. Part of the entertainment manager's job is to make risk-taking safer. But it is not safety per se that works, but the way it is provided. In discussing the notion of psychological safety, Edmonson (1999, p. 350) does not advocate "… a careless sense of permissiveness, nor an unrelentingly positive affect but, rather, a sense of confidence that the team will not *embarrass, reject, or punish* someone" for taking risks.

In sum, successful companies consider continuous changes, the taking of risks, and the challenging of routine approaches as integral parts of their culture. An entrepreneurial orientation makes a company more agile and ready to respond to changing market demands and new technological opportunities. And such an orientation needs to be part of a firm's DNA—it can't be imported from outsiders and consultants. An entrepreneurial orientation works best with the "right" people, which is why firms such as Netflix and Pixar put substantial effort into recruiting the best talent. And, as any cultural cornerstone, it should not be limited to a few, but be a pervasive element of culture that is shared by *all* members, from janitor to CEO. Look at Pixar, where all employees are encouraged to solicit suggestions, pose aggregated discussion topics, and work to implement solutions (Catmull and Wallace 2014).

Theme 4: Peer Culture Built on Candor and Trust

Open and candid communication among all organizational members, regardless of hierarchical level, is also a vital condition for creative innovation. The infinite possibilities that come with creating entertainment require the weighing of alternative options, and having multiple constructive perspectives available helps with that task. Each of us benefits from critical feedback—just like we rewrote each sentence of this book multiple times, it is rare (if not impossible) to find a screenplay whose initial draft was "the best."

Research provides strong evidence that such open communication only takes place when a culture is characterized by trust-based cooperative relations that exhibit mutual respect (e.g., Jucevicius 2010). Only in such a culture will team members encounter others in pursuit of solutions: to reveal problems, have candid, free, and open exchanges with people across levels of the firm, and to expose ideas to criticism (i.e., trying to get the right answer, not to win arguments).

The notion of psychological safety, mentioned earlier as an important condition for an entrepreneurial orientation, can only exist if people perceive mutual respect and trust among colleagues (Edmondson 1999). How can entertainment managers signal and support such respect and trust? Learning from the experiences of Pixar and Netflix, the key is to create a safe platform for offering ideas and thoughts, one which meets a number of criteria (see Hastings 2009 and Catmull and Wallace 2014). One criterion is that factors that inhibit candor must be carefully monitored and removed.

A second one refers to techniques and processes that can foster candor—they need to be established. But what are those "techniques"?

Pixar names "postmortems," or post hoc analyses of the reasons why a product has been a success or a failure, as an example. After a project has been completed, the company asks the team involved to name five things they would do again next time, along with five things they won't repeat. This is complemented with a detailed analysis of data about the various process steps—very much in line with the idea of *Entertainment Science* (see Catmull and Wallace 2014). Usually entertainment firms, driven by the "Nobody-Knows-Anything" mantra, do not see much value in such approaches: nobody likes being criticized, and there is nothing that can be learned from the last entertainment product anyway, is there? But powerful innovation depends on becoming used to open and critical debates on a daily basis. Let us note that no finite set of candor-ensuring techniques exists, and *cannot* exist: as soon as we, as employees, know a technique, we might find a routine to avoid its uncomfortable implications.

Finally, architecture also plays a role. Simply creating an environment in which people come into unstructured contact with others of differing backgrounds and views can lead to the serendipitous exchange of "seemingly unrelated bits of information" that can be the trigger for innovation. At Pixar, the Steve Jobs Building is constructed in a way that leads people from across function and hierarchy level to bump into each other and have conversations (Smith and Paquette 2010). Here and elsewhere, employees will take note and "get the message" that their bosses want them to exchange ideas.

Strategy and culture need a third force to enable powerful systematic innovation: the organization's foundational processes and structures, including the people who embody them. We will take a look at them now.

The Organizational Dimension of Entertainment Innovation

An entertainment firm's organization essentially consists of two key and interlinked aspects: *who* is part of the organization, and *how* do those members coordinate their efforts to create value? Let's take a look at them and at the ways they affect a firm's innovation performance.

The "Who" Question: The Importance of Human Resources

> "In procedural work, the best [people] are 2-times better than the average. In creative/inventive work, the best are 10-times better than the average."
> —*Netflix founder and CEO* Reed Hastings *(2009, p. 36)*

We have mentioned that highly talented people are fundamental to innovative entertainment enterprises. Such highly talented people are rare, as Mr. Hastings argues in this section's introductory quote above. So what do we know about the role of human resources management for successful entertainment innovation? Because innovations can be made, bought, or created in cooperation with others, we will address the management of both internal and external human resources in our discussion.

Internal Human Resources

Pixar has outperformed other entertainment firms with an approach that builds on the "in-house" development of all its projects. A pivotal aspect of the firm's approach to innovation has been the prioritization of talent over ideas. Pixar lives by the belief that if you give a mediocre team a brilliant idea, the transformation of the idea into a product will not live up to the promise of the idea; however, if you give an idea, even a mediocre one, to a brilliant team, the team will make it better, and often great. Thus, they focus on building a team comprised of the "right" people. The example of Toy Story 2 shows how the same story line can result in outcomes that differ dramatically in quality when executed by teams of differing abilities (Catmull and Wallace 2014; p. 379).

So a focus on attracting and retaining top-flight talent in the internal entertainment innovation operation is recommended. But what characterizes such talent? Netflix, who puts a similarly strong emphasis on internal personnel, prioritizes mature people, acting under the assumption that brilliant "rookies" are more costly for the firm than what they are worth in comparison (Hastings 2009). Further, they regularly employ the "Keepers Test," a mental exercise that asks a manager to consider how hard they would fight to keep an employee if that employee announced an intention to leave. If you wouldn't fight hard to keep a person, perhaps it is best to cut them loose and hire someone you would fight to keep.

But the management of human resources for innovation is not limited to hiring decisions. Another way to boost performance is to provide opportunities for development and support to key creative people, recognizing that what these people might be able to do tomorrow is more important than what they can do today. Employees with high innovation capabilities and high intrinsic motivation will exhibit a willingness to learn new things and grow their own creative innovation capabilities—and the firm's (Savitskaya and Järvi 2012).

The individuals and their respective skills are important, but there is more that needs to be considered. We have already stated that across entertainment it is usually the coordinated efforts of a *team* that results in new entertainment products that win in the marketplace, which is why Pixar's focus is on brilliant *team* performances rather than on brilliant individuals. Teams are more than the accumulation of great skills—their output requires ongoing coordination, which depends on social harmony. Narayan and Kadiyali (2016) provide empirical evidence for the role of a creative team's composition with dynamic panel data estimations of interactions between members of production teams of 1,123 movies. Studying weekly North American box-office revenues with a GMM regression, they find that the shared previous experiences between a film's producer and other team members are most impactful for a film's success. Interestingly, it is not the *success* of earlier collaborations that matters, but the mere existence of a social connection between them that results from having collaborated in the past.

A related question is whether creating an internal team that is highly diverse in background and orientation is beneficial for innovation. Evidence is fairly anecdotal so far and exists for both perspectives—diversity has been argued to bring benefits of serendipity (Smith and Paquette 2010), whereas homogeneity has been associated with creative synergy (Harvey 2014). We argue, based on our discussion of the critical role of culture and the different goals associated with the creation of entertainment, that the benefits of diversity end when diversity exists regarding fundamental values or goals (see Gilson 2015 for a discussion).

External Human Resources

For creating innovations, it can also be beneficial to maintain a network of cooperation with resources *outside* the firm. Packard et al. (2015) study empirically two aspects of such cooperation: the degree to which a creative is tied to prominent others in the industry (which might help the reputation of the projects he or she is working on among consumers) and the degree to which the creative maintains connections with other "sub-communities" in the industry (which might provide access to unique skills and resources). In an analysis of 15,000 movie professionals and the performance of their films with regression analysis (in which they control statistically for several other "success drivers"), the scholars find that both kinds of networks can help—but for different groups of creatives. Specifically, whereas ties with prominent others ("high positional embeddedness") exert a positive influence on a movie's box office performance for creatives who are part of the onscreen cast (i.e., actors), maintaining bridges and thus access to other segments of the industry (or "high junctional embeddedness") pays off for members of the behind-the-screen crew (including directors and producers).

Academia plays a particular role for such outside networks—one that is neglected by many. For example, Pixar values close connections to the outside world, sharing their early work on computer animation with the scholarly world (e.g., through publications and conference presentations), instead of cloaking it in secrecy like other companies. This participation in the intellectual discourse has also taken place in other academic fields such as business, and our numerous references to Pixar and its approaches in this book give evidence of it. Though the exact impact of this sharing is difficult to pinpoint, connections with information technology scholars were formed over time and have been named as valuable for fueling innovation and the firm's understanding of creativity (Catmull and Wallace 2014).

Netflix, too, practices active ties to the academic community. We give evidence of it at various points of this book, such as when discussing their $1 million recommender algorithm competition known as the Netflix Prize, as well as their contributions to the academic discussion on recommenders (e.g., Gomez-Uribe and Hunt 2015) and movie trailers (Liu et al. 2018). The company also worked together with cultural anthropologist Grant McCracken to gain deeper insights into consumers and the "spoiler" phenomenon (Steel 2014). Particularly in times characterized by high dynamics, such connections can allow a firm to overcome traditional restrictions and problem-solving patterns by thinking "out of the box." As we have noted earlier in this book, we have come under the impression that such openness to outsiders and scholars, in particular, is not strongly developed among many traditional producers of entertainment.

At the end of the day, an entertainment manager's job must be to bring the *right people* together, combining internal and external talent, to construct a team that complements each other and works collaboratively toward the pursuit of shared goals.

The "How" Question: Creativity Needs Freedom

> "I am a firm believer of the chaotic nature of the creative process needing to be chaotic. If we put too much structure on it, we kill it. So there's a fine balance between providing some structure and safety—financial and emotional—but also letting it get messy and stay messy for a while."
>
> —*Pixar-Executive* Ed Catmull *(quoted in* Catmull *and* Wallace *2014, p. 142)*

Assuming you have assembled the right team of creatives, what kind of organizational structure will allow them to flourish and create high-quality entertainment innovations? In the introductory quote above, Mr. Catmull stresses that creativity is inherently chaotic, which implies that the structure of innovation processes must be designed in a way that accounts for such chaos, leaving room for it while, at the same time, preventing escalation. This is also in line with the "micromanagement threat" for innovation we noted earlier.

Based on our review and analysis, we argue that a good organizational design for supporting innovation must meet the following three conditions: (1) it requires a relatively "flat" organizational structure to facilitate communication and decision making, (2) it must leave room for failure to happen in the *early* phases of the innovation process to allow quick adaptations in case of failure and minimize the economic consequences, and (3) it must avoid over-structuring, in the case a company grows, to not harm innovation processes. Let's see what kinds of organizational approaches are helpful for meeting these requirements.

Condition 1: (Relatively) Flat Hierarchical Structures

To enable free-flowing communication and quick, effective decision making, there is evidence for the advantageous nature of flat organization structures for innovation activities. A flat structure supports communication and decision making in several ways:

- it reduces bureaucracy levels (e.g., Archer and Walczyk 2006);
- it avoids a restrictive vertical chain of command (with "top-down" dictates and no exchange of thoughts and ideas between members of the firm) and restrictive roadblocks to change (e.g., Kanter 1997);
- it avoids rigid routines and supports flexibility in terms of when or where to work (e.g., Savitskaya and Järvi 2012); and

- it offers more decision-making options as a reward for good performance (e.g., Archer and Walczyk 2006).

When the "right" people are given big jobs along with the authority and responsibility to work together to be innovative, good results normally happen when there is no excessive hierarchy to keep them from doing so. One powerful example for a flat hierarchical structure for innovation activities is Google, where communication is seen as peer-to-peer rather than manager-to-minion (Hamel 2006).

To enable the best ideas to bubble up regardless of where they occur within the firm, job titles and hierarchy are relatively meaningless at Pixar, with unhindered communication being a core structuring principle (Rao et al. 2008). One specific mechanism to insure this open communication across a flat structure at Pixar is named "Braintrust"—an ad hoc, problem-solving unit formed to analyze the emotional aspects of a story without getting emotional (Catmull and Wallace 2014). Braintrust transitioned from a fixed group of senior people to a larger group of people that assemble as needed to solve concrete problems—the best ideas get challenged and tested.[261] An important credo within the Braintrust is that the person who proposes an idea is separated from that idea during the debate, which supports candor and honesty in the spirit of constructive criticism. The approach does not magically solve all problems, but it can help recognize when something is off.

In addition, there are no mandatory notes handed down from executives to directors at Pixar, as is common in most traditional entertainment firms. Instead, it is the responsibility of a director to make a good movie and he/she is trusted with figuring out how to accomplish the goal. However, this does not mean that the whole system is *laissez-faire* until the end—if a team is truly stuck, the rules then require changing the team. Which turns out to be not such a rare occurrence after all at Pixar—the initial director was not only substituted in Toy Story 2, but in five out of the firm's first 18 films, or 28% of the projects (Spiegel 2013).[262]

But how do you steer people in entertainment while employing a "hands-off" approach implied by flat hierarchies? With Netflix in mind, Hastings (2009) argues that management should be done through context, not

[261] Any scholar will be reminded of the ideal version of the peer-review process in academia.

[262] Flat structures and open communication should not be confused with eternal harmony: at least four of the five substituted director were no longer with Pixar in 2013 (Spiegel 2013).

control, putting emphasis on some of those aspects of innovation management we have mentioned earlier in this chapter, such as strategy (including accurate assumptions and objectives), culture, success metrics, and people. This view is consistent with general scholarly research on creativity and innovation that finds that performance is enhanced when goals are provided to talented people with creative thinking skills, but they are given as much autonomy as possible concerning *how* to achieve the goal (e.g., Walesh 2012).

Condition 2: Leave Room for Failure in the Early Phase of the Innovation Process (Only)

Careful planning is difficult in the realm of creativity with the limitless number of potential combinations of elements in an entertainment product innovation. Errors are somewhat unavoidable for the firm that is pushing forward and trying to accomplish something great. Managers cannot avoid missteps; however, they can design the innovation process in a way that biases failures toward the *early* stages of the process.

Doing so is crucial from an economic perspective, because the costs associated with wrong-doing are not equally distributed over the course of the process. Instead, costs escalate in later stages, increasing exponentially from the creation of ideas, through the formulation of the product concept, to the production of the actual product. Underlying this exponential cost development is an inverse, non-linear reduction in the firm's flexibility to make changes to the project over time, as we display in Fig. 10.6.

And what kind of structures help to shift errors toward the front-end of the process? One potential response is the so-called "loose-tight" concept, which suggests that the organization of the innovation process should be designed loosely in the early stages, leaving large room for creatives to experiment (e.g., Albers and Eggers 1991). In the later stages, however, the concept suggests a change toward a more restrictive form of process management, in which creatives are provided much less room for changing the product idea and concept. In other words, efficiency and project implementation are prioritized over creativity in the later stage. We have to note though that the loose-tight concept has so far received only partial empirical support and has not been tested in an entertainment context.

A different approach that has been suggested to minimize the impact of failure is to focus on the speed of making changes and adjustments to the product concept during the process by creating a "high-velocity environment."

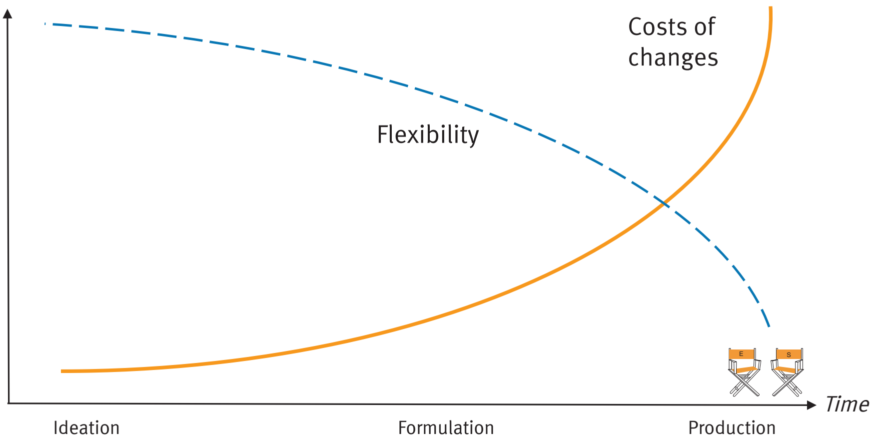

Fig. 10.6 Escalating costs of failure during the innovation process
Note: Authors' own illustration.

Netflix, for example, operates under a "rapid recovery" model that is based on the assumption that it is better to learn and fix errors than to prevent them from happening in the first place. Keep in mind, though, that such a model conflicts with the cost development we describe in the figure above and that is so typical for innovation processes; its use might thus fit better with some entertainment innovations (e.g., the adding of features to online games) than others (e.g., the development of a big-budget movie or series). Finally, *Entertainment Science* scholars have accumulated evidence that thorough testing in the early stages of the innovation can be a powerful way to meet this condition in a satisfying way, despite the industry's traditional skepticism toward it.

Condition 3: Avoid Over-Structuring When Growing

Success makes an organization grow, which is inherently a good thing. For innovation, however, growth introduces additional challenges. Growth brings an increased complexity because of the higher number of individual workers whose efforts must now be coordinated, and because a growing firm usually manages a higher number of projects and/or product lines simultaneously. Look at Pixar, which has moved from a biannual release schedule to now releasing two new films each year. As firms grow, a tendency exists to institutionalize vertical chains of command, put in place formal (and often rigid) policies and procedures, control employees communications and access to resources, and create approval processes that may improve efficiency (e.g., Kanter 1997)—essentially all those things we have argued in this chapter should be avoided to the degree possible in entertainment innovation.

Netflix's Reed Hastings (2009) argues that hiring additional high-performance employees provides the solution to this organizational challenge—they are motivated, and able, to maneuver the innovation process themselves, without the need for additional structures and bureaucracy. To assist such people in operating a growing organization informally, Netflix works to minimize structures whenever possible. For example, they focus on a few big products instead of many small ones. The firm also systematically works to eliminate distracting complexity that comes in the form of process-focused policies that might have worthy goals, but saddle employees with onerous compliance burdens or restrict their agility.

Overall, our conclusion, based on scholarly research and anecdotal evidence from growing entertainment firms, is that there are certain strategic, cultural, and structural parameters that determine creativity and innovation. The complete process—from initial idea to finished product—is inherently chaotic and involves at least a few errors. Attempts to formalize the process can quickly devolve into micromanagement and risk avoidance, approaches that are, overall, bad for the performance of an entertainment firm. Improving processes must not be the main goal; the main goal is making the product great or achieving whatever goal a firm has set.

At the same time, although freedom is foundational for creativity, freedom cannot be unlimited. Some rules are necessary, such as those to prevent irrevocable disaster and those that relate to moral, ethical and legal issues. We like Mr. Hastings' (2009) distinction between "good" processes (those which empower talented people to get more done and help them avoid serious missteps) and "bad" processes (those that incur high costs of time and/or frustration to prevent mistakes that are, in reality, easy to rectify if they occur). We believe that most readers of this book, regardless of their background, will be able think of examples where budget management policies were "good" (e.g., spend a proportion of budget without asking for permission) and where they were "bad" (e.g., requiring multiple layers of approval for routine repurchases). The goal must be to create operational policies that are highly aligned with goals and enable flexibility and creativity for those working within it.

Let us now move away from the innovation-related matters that take place at the company level and take a look at actions that deal with a specific new product idea: how the use of smart forecasting of an innovation's performance can help firms turn an idea into a successful new entertainment product.

The Product Level: How to Forecast the Success of New Entertainment Products

> "If my fanny squirms, it's bad. If my fanny doesn't squirm, it's good. It's as simple as that."
>
> —Harry Cohn, *founder and president of Columbia Pictures from 1919–1958, describing how he predicted the success of a new movie (quoted in* Austin *1989, p. 1f.)*

For any new product, whether internally developed, co-produced, or externally acquired, a need exists to forecast the success potential of the respective idea, concept, or product. Success predictions are needed for green-lighting a concept, to guide substantive pre-release changes to a product, and to allocate budgets to an innovation that are in line with its commercial prospects, an essential facet to the long-term health of any business.

We are convinced that managerial intuition (in the way used by the legendary Mr. Cohn in the quote above, or somewhat more subtly), can help with such predictions. However, a central theme of this book is that a manager's experience-based judgment can quite often be supplemented with *Entertainment Science*, i.e., the thorough combined use of theory and data, to the manager's advantage. We argue this to particularly be the case for the prediction of the success of innovations. In this section, we describe how such support can come in the form of econometric prediction models. Like any part of *Entertainment Science*, innovation prediction models should be seen as complementary to, not as substitutes for, decisions based on hard-earned managerial intuition.

Entertainment Science scholars have developed various approaches for using existing data for predicting the success of new entertainment products. These approaches differ in several ways—most importantly with regard to the econometric method used and the data employed. Data availability differs between the stages of innovation processes, and so do prediction models that are applied in the early conceptual phase of entertainment products differ from others which are used in the crucial pre-release phase shortly before release, and also from early post-release models that incorporate initial sales data.

After a short primer on the essentials of success prediction, we will overview the key prediction methods, namely feature-based and diffusion-based models, before we illustrate the use of predictions at different points of the innovation process. We will restrict our discussion strictly to the methods and fit of predictions, but refer to the other, substantive chapters of this book for a discussion of the predictor variables themselves. As in other areas of *Entertainment Science*, most research we report uses movies, but insight should be usable with some modifications for any entertainment product for which similar data is available. And what about predictions offered by consultants and made by entertainment firms? For the most part, we will leave them aside, because they usually lack information about the method and their goodness of fit, things that we consider essential for any kind of useful prediction.

Some Words on the Essentials of Success Prediction

Regardless of the specific analysis method used, success prediction studies in entertainment rely on a pattern that comprises four steps: (1) choosing the predictors, (2) choosing the prediction objects and the data sources, (3) running the analysis using the holdout-sample approach, and finally (4) assessing the quality of the forecasts. Let us take a closer look, step by step.

Step 1: Choosing the predictors. The first step in any prediction analysis is to determine the variables that will be used for the forecasts. A key question here is whether to restrict the set of predictors to those variables for which causality has been demonstrated (or can at least be argued to exist), or to allow *any* kind of variable to serve as a predictor if it helps the prediction to be more "accurate" (a *terminus technicus*; see below what it means in a prediction context). For most of the marketing variables we have presented in the various chapters of this book's Part II, from quality to different forms of pricing, we argue that they indeed have a causal relationship with success.[263]

But in these times of abundant data availability, there is a lot of additional information out there that could also be used in prediction tasks, and several prediction analysis conducted by scholars do indeed include them. We have one very clear recommendation for every entertainment manager though: stay away from predictors for which you cannot claim a causal effect. Using them might work in the short-term, but it can lead those who apply them into serious trouble once the measurement, the meaning, the usage, or the context of that predictor changes. In the face of environmental change,

[263]But this causal nature should not be taken lightly.

including variables without a clear causal explanation can result in substantial under- or overpredictions—and corresponding misallocations of marketing budgets, or plain wrong decisions. Further, we argue that the same care is suitable for methods that are "black boxes" with regard the *course* by which the predictors and success are linked. Unknown or arbitrary functions can lead to serious mispredictions if your predictor takes new values, outside the original spectrum or even within it. Do not trade in causation (or at least its justified assumption) for some supposed formal increase in accuracy; in the long run, chances are that it will turn out to be an artifact and lead you toward bad decisions.

If you follow our recommendation, this book provides a sourcebook for selecting powerful predictors. Their availability will vary between prediction tasks, and not all will be equally relevant—there is a tradeoff between the increase in prediction accuracy another predictor adds and the costs for collecting the respective information. But keep in mind the fundamental logic of this book, and of *Entertainment Science* in general, when selecting prediction variables: the better the model reflects what is actually going on in the market and the consumer, the more powerful the prediction will be.

Step 2: Choosing the prediction objects and collecting the data. Before data collection can commence, the researcher has to answer the question: "For what object(s) do we want to predict success?" The answer can range from trying to predict the success of a single product (e.g., as Eliashberg et al. 2000 predict, and measure, the performance of the movie Shadow Conspiracy in Rotterdam theaters) to trying to establish a model applicable to *any* product in an entertainment category (e.g., any movie). There's no right or wrong—the choice of the object(s) is determined by the strategic decisions that need to be made based on the prediction. But the choice of the object influences the adequacy of the prediction approach.

Regarding the data itself, predictions can be made based on secondary data (which exist separately from the prediction analysis) and primary data (which is collected specifically for the analysis); these types of data can be used separately or in combination. Secondary data is widely available in entertainment and can be either accessed freely for many usages (via websites such as IMDb, Google Trends, or Facebook's API) or purchased (from services such as Kantar, Rentrak, or Linkfluence); its advantage is that it is readily available for collection and for analysis. But secondary data often has limits, as it often contains "missings," and the quality of the available data is not easily verifiable (such as for production budgets). Also, keep in mind that secondary data is always historic data (about something that has already happened, either years or seconds ago), so its usefulness for predictions of things *to* happen in the future depends on whether the context from which it stems will still be valid. The alternative is primary data, whose collection can consume enormous resources (such as when done via surveys or panels) and can suffer from quality problems itself (do respondents tell the truth?). However, primary data can be exclusive when collected by a company itself and its collection can be designed specifically to meet the prediction task's demands. But depending on resources, exclusivity can also exist for secondary data—think of Netflix's viewer statistics and individual usage patterns. Some of the best prediction models combine both kinds of data.

Step 3: Running the analysis using the holdout-sample approach. A key question for making predictions is to pick the "right" econometric method; we name some key alternatives that can be used in the context of entertainment below. One important component of predictions is the "holdout" approach. The approach's idea is intuitive: when the analyst does not want to wait for predicted events that lie in the future to happen, he or she selects a subset of the objects from historic data and puts this "holdout sample" aside until later in the analysis. The remaining objects are used to "train" the prediction model, and its goodness of fit is judged against how well it "predicts" the objects in the holdout sample. If all available objects are used for training and evaluation, the prediction results are biased toward the positive and are thus only meaningful for the objects in the data set that was used for calibrating the model. Selecting a holdout sample is far from a trivial task: the way it is done affects the fit of the prediction model.

Step 4: Assessing the quality of the forecasts. To assess the "goodness of fit" of a prediction, researchers rely on several accuracy metrics. There is not a single "best" one; instead each of them brings its own limitations of which the user should be aware. Among the most common metrics are the Mean Absolute Error (MAE), the Root/Mean Squared Error (R/MSE), and the Mean Absolute Percentage Error (MAPE). Whereas both the MAE and the R/MSE compare *absolute* differences between predicted and actual values, the MAPE compares *relative* (percentage) differences.

The MAE describes the average absolute difference between a predicted value and the corresponding actual value for the success metric (such as a film's box office). As an absolute value, it depends heavily upon the magnitude of the chosen success metric. If you have one Avatar in your data whose performance your model cannot predict correctly, the mean error will be quite high, even if the model works fine for all other films in the data set. In contrast, it doesn't matter much if the smaller products in a data set are predicted wrongly, even if these errors are high percentage-wise. The R/MSE builds on the logic of the MAE; it is the square root of the sum of the squared deviations of all predicted and actual values in the data set. As the measure penalizes prediction outliers by squaring, it is of most use when large prediction errors for single cases are particularly undesirable (and a higher, but more equally distributed prediction error is preferred over drastic fails for certain cases).

MAPE is the average prediction error measured in percent; it is intuitive, but can be influenced strongly by the error of smaller absolute values, and it penalizes extreme upward deviations more strongly than for lower deviations (the former can be—much—higher than 100%, the latter cannot). Whether to use an absolute or relative criterion depends on the user's preference—if the objects in the data are of similar importance despite their differences in absolute success, then a relative criterion makes more sense. If the bigger hits are more important for the firm, then it should be an absolute criterion instead. Having a Blair Witch Project in the data set, which generates 100-times the expected returns, drastically inflates relative accuracy metrics such as the MAPE, in particular.

Prediction Methods: Feature-Based Versus Diffusion-Based Success Prediction

At the heart of any prediction task is the statistical algorithm that transforms the values of the predictor variables into forecasts. Entertainment scholars (and managers) can chose between a plethora of specific prediction methods, but the underlying more fundamental decision is whether to pursue a "feature-based" or a "diffusion-based" approach. Feature-based predictions combine knowledge about the predictors of entertainment success, namely the different "success drivers" we discuss in this book (such as product characteristics like story elements or quality or ad spending), and generate predictions based on linear or non-linear transformation functions.

Diffusion-based predictions, in contrast, use theoretical models of how entertainment products diffuse among consumers over time. Neither type of approach is generally superior; their effectiveness depends on how well the user understands the linkage between features and success or products' diffusion patterns, respectively. We will now overview the most prominent techniques for both approaches, starting with feature-based predictions.

Feature-Based Approaches of Success Prediction

The most-employed feature-based prediction method is regression analysis, along with its many extensions. A second important stream consists of methods powered by machine learning, such as neural networks and decision trees.

The majority of the causal insights on how marketing variables drive entertainment success that we report throughout this book stems from regression-type analyses, which is why we discussed the foundations of the method in the book's introductory section. In a nutshell, regression analysis assumes and estimates a systematic (often linear) relationship between one or more independent variables and a dependent (or outcome) variable. Regression uses an optimization process that minimizes a measure of how much deviation there is between the observed data points and those that are calculated by the estimated regression function.

But in addition to explaining relationships, regression also provides everything the user needs for a *prediction* task: a regression function allows the user to predict the success of an entertainment product by entering specific values in the function. Explanation and prediction with regression analysis are methodically the same; they differ with regard to the intentions of the user and if the causality assumption is waived when making predictions. Scholars occasionally blur the distinction, speaking of predicting when the actual goal is to gain causal understanding (e.g., Litman 1983; Simonoff and Sparrow 2000; Chang and Ki 2005).

An alternative approach for making predictions is to use machine learning. Machine learning has become something of a buzz word (Gartner 2016), but the concept is not quite as well-understood by the public and industry as the term is familiar to them. Broadly speaking, machine learning encompasses algorithms that can learn from data and, through optimization routines and multiple iterations, find the "best" analytical solution for a given question (e.g., Brownlee et al. 2013; Kohavi and Provost 1998). Predictions are just one application for machine learning, a family of approaches that sprouted from the artificial intelligence community.

Models that are used in success predictions tend to belong to the category of *supervised* machine learning—because the predictors and success variables are pre-specified (e.g., Kelleher et al. 2015). Machine learning can offer stunning fit values, which, however, come at a price for the entertainment manager: the approach tends to treat the world as a "black box," with little emphasis on reliable explanation of causes and effects (see Breiman 2001 on statistical modeling cultures). We have already mentioned the problems that can result from such an approach—and kindly ask our reader to keep them in mind.

One stream of machine learning for which these concerns are particularly valid uses artificial neural networks, methods that attempt to represent mathematically the same type of information processing that occurs in our biological brain system.[264] Neural networks consist of artificial neurons that are arranged in layers and interconnected. Given a certain set of input variables, corresponding nodes get activated in the following layer, which then activate certain nodes in the next layer (and so on, depending on the number of layers). The unique set of activated neurons in the last layer provide a solution.

Sharda and Delen (2006) are among those who applied the method to predicting entertainment product success. Their model is based on 834 movies released in North America between 1998 and 2002 and data for several marketing variables we discuss in this book (e.g., MPAA rating, competition, star power). They report that their model correctly assigns about three out of four films into one out of nine success categories (or to one of two categories that are directly contiguous to the correct category). However, sensitivity analyses show that variables like competition, MPAA ratings, and most genres, whose influential role we have explained and empirically demonstrated in this book, play no role in their estimation. This result should raise plausibility concerns—and underlines our caution regarding prediction methods that model the complex links between predictors and entertainment success in a solely data-driven way, using black boxes instead of theoretical considerations.[265]

A second stream of machine learning techniques are called "decision trees." They work through a sequence of questions that have categorical answers (e.g., yes/no, high/medium/low, values above/below a certain value) to arrive at a mathematically optimal solution; continuous variables have to be categorized to become part of the process (see Kelleher et al. 2015 for an overview). A first categorical variable considered in a decision tree is called the "root," or "starting node." The decision tree then asks which potential value the variable has taken on, and for each possible answer or variable manifestation the node splits to consider further variable questions. These

[264]Please see Algobeans (2016) for a more accessible description of artificial neural networks and Bishop (2006) for a more technical overview.

[265]We have similar issues with other studies that predict box office using neural networks, such as Sharda and Delen (2010), Ghiassi et al. (2014), and Zhou et al. (2017).

next layers are called interior nodes. Some variables contain more information than others and can help the algorithm progress more quickly. After working through all interior nodes, the model will eventually reach a conclusion, called the "leaf" (or "terminating node").

In entertainment, decision trees have been used to predict the commercial success of films (e.g., Eliashberg et al. 2007; Parimi and Caragea 2013),[266] as well as for how much consumers will like a film (Asad et al. 2012). In addition to the black box problem for the links, decision trees tend to have stability issues, with the choice of the root impacting the solution. Interpretation and stability are particular issues when either many variable categories or continuous variables are used, which are clearly the norms when predicting the success of entertainment products, as this book demonstrates.

Diffusion-Based Approaches of Success Prediction

Based on the notion that the patterns of revenues generated over the lifetime of entertainment products "display remarkable empirical regularity" (Sawhney and Eliashberg 1996, p. 113), scholars have drawn on the diffusion literature to explain, in a theoretically meaningful way, the empirical diffusion patterns of entertainment products and, ultimately, to forecast their future success. Let us explain the basic logic of diffusion-based predictions by drawing on the fundamental diffusion model by marketing scholar Frank Bass (1969) before highlighting key learnings from the empirical application of diffusion models to entertainment products.

The "Bass Model" of Diffusion

Frank Bass' basic idea was that there are two primary segments of customers in any market that drive the diffusion of a new product: Innovators and Imitators. According to his model, Innovators are those consumers who are drawn to new innovations, willing to take risks and deal with uncertainties. Most importantly, these consumers adopt a new product independent of other people's actions, such as word of mouth. Most of these Innovators gain access to a new product early on; the number of Innovators still available to

[266] Josh Eliashberg and his colleagues apply the method in their analysis of movie script features, whereas Parimi and Caragea use it for a general prediction exercise.

adopt the new product for the first time decreases quickly for a successful product.

Imitators, in contrast, are more risk-averse and will not tend to adopt new products until some of the uncertainties surrounding technology issues and market acceptance are reduced; thus, they tend to observe Innovators' behaviors and learn from those behaviors. Imitators make decisions based on the behaviors of—and word of mouth from—the part of the population that has already adopted the product. They do not adopt the product at its launch, but only begin to adopt the new product as they eventually copy or learn from the behaviors of the Innovators and other Imitators who have already experienced the product.

The Bass model features parameters for the adoption behavior of each of these two consumer groups and describes the two groups' respective contributions to a product's diffusion over time, as well as the links between them. The innovation parameter, or α, represents the reactions of Innovators when a new product becomes available and how they generate revenues over the diffusion process, and the imitation or word-of-mouth parameter β captures the behavior of the Imitators. According to Bass, the number x of a new product sold in a time period t follows the following pattern:

$$X_t = \alpha \times \left(\bar{Y} - Y_{t-1}\right) + \beta \times \frac{Y_{t-1}}{\bar{Y}} \times \left(\bar{Y} - Y_{t-1}\right)$$

where X_t is the total number of units of the new product that are sold in period t, $\bar{Y}$ is the number of potential buyers of the new product (or the "market size"), and Y_{t-1} is the number of buyers who have already purchased the new product by the end of the *previous* time period. The equation shows that the segments of Innovators and Imitators affect adoption in a largely additive way; however, as their respective sizes influence the number of adopters up to a given point in time Y_{t-1}, a higher β reduces the number of products that will be sold to Innovators in the next period. The effect of a higher α on the number of products sold to Imitators is less straightforward—on the one hand, a higher α reduces the number of products that are left for Imitators, but on the other it increases the chance that Imitators are influenced by word of mouth from those who have already adopted the product.

At its core, the Bass diffusion model (like all other diffusion models) uses statistical distribution functions; the response of Innovators follows an exponential distribution, whereas the adoption by imitators describes a logistic distribution. By combining these distributions, the model offers substantial flexibility; it provides room for a number of different patterns, depending on the value of the specific parameters for the innovation parameter α, the imitation parameter β, and also Y, as the number of total buyers. In Fig. 10.7 we illustrate this flexibility by showing the diffusion patterns the model calculates for four different combinations of α and β.

Whereas the upper left pattern (Panel A) exemplifies a new product with a relatively low innovation parameter and a moderate imitation parameter, the upper right pattern (Panel B) shows how diffusion changes when a product appeals more strongly to innovators; that trend is illustrated with an even more radical example in the lower left part of the figure (Panel C). Finally, the lower right pattern (Panel D) has the same innovation parameter as the one above it, but shows the impact of a higher imitation level.

The figure also illustrates that the two diffusion parameters of the Bass model are closely tied to the concepts of marketability and playability that

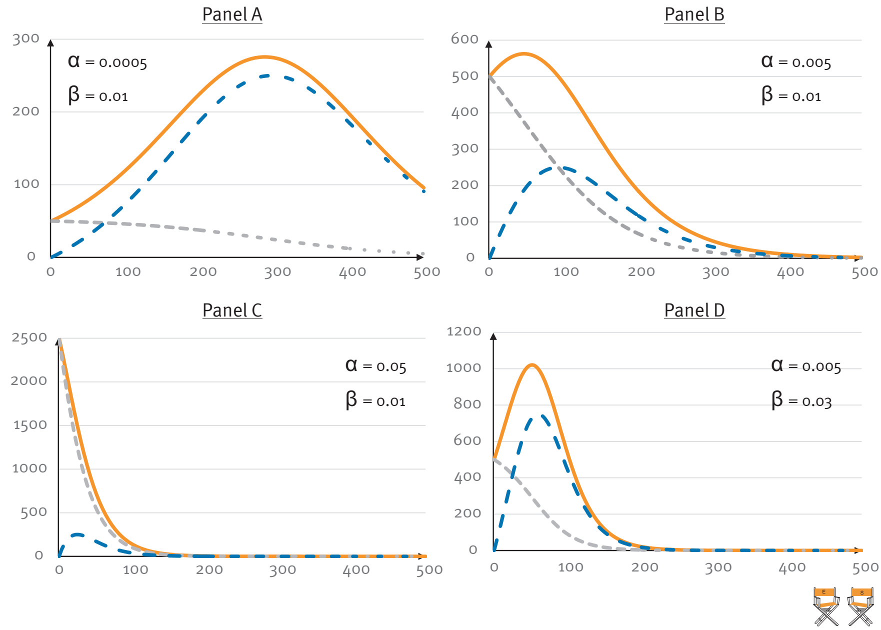

Fig. 10.7 Adoption patterns for different combinations of innovation and imitation parameters

Notes: Authors' own illustration based on the diffusion model by Bass (1969). All patterns in the figure assume a market potential of 100,000 units for the new product and study sales during the products initial 500 days. The straight orange line indicates the total adoption of the new product; the dashed blue line shows the adoption by Imitators only and the dotted grey line are Innovator adopters only. All data is hypothetical.

we discussed earlier. Specifically, as can be seen in the figure by comparing the upper and the lower left pattern, a higher innovation parameter leads the function to peak earlier, because a large number of consumers adopt the product independent of quality-related recommendations from friends or others—which is essentially the same as high *marketability*. In contrast, a higher imitation parameter reduces the time needed for word of mouth about a new product to spread among consumers, because a large number of consumers choose the product based on quality recommendations from friends and others—the equivalent to high *playability* of an entertainment product. Statistically, if α is larger than β, the total sales function (the orange line in the figure) follows an exponential distribution (which is typical for entertainment blockbusters, see this book's chapter on integrated marketing strategies), whereas if β is larger than α, the function follows a logistic distribution (which is typical for "niche" products).

Both the innovation and imitation parameters of the Bass model, as well as the total sales volume, can be estimated using either early historical sales data from similar products or from early sales data of the new product and then applying regression analysis to them. If sufficient parameters of the model are already known, the equation can be used to solve for the missing one. Clearly, the quality of the forecasted adoption pattern depends on the quality of these inputs. If there are no reasonable "comparables" for which data is available, then the quality of the output will be lower. The version of the Bass model we have described here does not account for marketing strategies and interventions that may alter market acceptance of the new product. However, Frank Bass himself and also other scholars have advanced the model in several ways, including the provision of room for marketing actions (e.g., Muller et al. 2009 provide an overview).

Applying Diffusion Models to Entertainment Products

Whereas the Bass model was originally developed with consumer durables (such as TVs and lawn mowers) in mind, *Entertainment Science* scholars have developed diffusion models which are attuned to the peculiarities of entertainment products. A prominent example is BOXMOD, a diffusion model that Sawhney and Eliashberg (1996) developed with movies in mind. At the heart of BOXMOD is the assumption that an individual consumer's time to adopt a movie is the sum of (a) the time he or she needs to *decide* to see the movie (based on available information) and (b) the time he or she needs to *act* on that decision (i.e. to actually go out and see it).

Depending on these parameters, the observed diffusion follows different patterns again, which in this case include an exponential distribution and a Generalized Gamma distribution. Combining the two parameters with the estimated market potential of a movie, Sawhney and Eliashberg developed a diffusion model which requires three weeks of success data to generate forecasts, as well as an extended version which also incorporates the "supply side" (i.e., the number of theaters in which a film was shown in a given week).[267] To be of use *prior* to a film's release, firms would need to anticipate the two key parameters of the model, relying on experience and/or the historical results of comparable movies.

Combining their diffusion-based prediction approach with the feature-based approach by linking their diffusion parameters with certain movie characteristics (such as star power, MPAA rating, sequel, professional reviews, and genres), Sawhney and Eliashberg explain about 12% of the variation of their "time-to-decide" parameter and about 22% of their "time-to-act" parameter with regression analysis (and 42% of their total sales variable).

In a separate study, Ainslie et al. (2005) suggest an alternative approach to BOXMOD. Their diffusion model for movies assumes a Gamma distribution and uses three parameters, namely (a) the expected attractiveness of a film in its opening week, (b) the point in time when the film's distribution peaks, and (c) a "speed" parameter that reflects the speed with which a movie's attractiveness builds and decays. Like Sawhney and Eliashberg, Ainslie et al. also integrate the feature-based approach by linking their parameters with movie characteristics, for example star power and professional reviews. They further make an attempt to integrate "market" forces such as distribution and timing effects,[268] as well as competition, into their forecasts and estimate it with an approach known as a "Markov Chain Monte Carlo," or MCMC, algorithm (which essentially estimates switching probabilities from one phase to another by drawing samples of data).

When Ainslie et al. applied their model to predict the *total* box office of 404 movies released in North American theaters from 1995 to 1998, they calculate a MAPE of just 6% when using only demand factors, and of below 4% when adding in information on "market" forces. Their estimations for

[267]A separate approach to include distribution into a model of movie diffusion is the approach by Jones (1991), who essentially suggests a modification of the Bass model.

[268]A study by Radas and Shugan (1998) focuses on how seasonal variations of demand for entertainment could be embedded in diffusion models. Please see our chapter on entertainment distribution decisions for a discussion of the impact of products' release timing on success.

the basic Bass model and the BOXMOD model are comparable. Predictions become clearly less accurate, though, if used to predict the films' *opening weekend* box office results. Here, the Ainslie et al. model has a MAPE of 33% (remember that it also uses product features), whereas the MAPEs for BOXMOD and Bass are four- and five times higher, respectively. When performing a kind of out-of-sample analysis (using only data for the weeks up until the week prior to the prediction), the MAPE of their model worsens to 74%, as do those for Bass and BOXMOD. The importance of what kind of information is used to calibrate the prediction model is also visible when Sawhney and Eliashberg estimate their model for 111 movies from 1992 (and using a holdout set of ten movies). Whereas using movie characteristics only shows a decent MAPE of 71%, including one week of sales reduces this error to 52%, and including three weeks of sales data result in a MAPE of only 7.2%.

You, our reader, might wonder: are these levels of error too high for the models to be of *any* use at all? Whereas more accurate models are clearly desirable, their value is not really gauged by an absolute error number; instead, the true comparison is to having to take action without *any* such information. These MAPEs indicate that the best prediction models are far better than chance or than having *no* information. As is commonly said, a good forecasting model is like using your headlights when driving a car at night; your vision of the road ahead is not perfect, but it is far better than it would be without headlights.

With the available information obviously being a crucial factor for the effective use of prediction models, let us now take a look into the critical points in time for a manager to make success predictions—and the respective requirements for these models.

The "When" of Success Predictions: Early Versus Later Approaches

Early-Stage Predictions for Entertainment Products

An initial key point in time for making success predictions is when an entertainment product is still in its idea or concept phase—relatively little money has been spent so far for its development, and valid information on the product's success potential can either enable the firm to greenlight a huge hit or save a lot of money from being wasted. At this point, predictions can be made based on a product idea's genre and content elements (such as the script of a movie), and its brand characteristics, among others.

For each of these variables, our book describes studies that have empirically explored their role for product success—see, as just one example, the studies of Eliashberg and his colleagues on the role of movie scripts. Netflix used econometric analyses to predict the appeal of the House of Cards to its subscribers at an early stage based on the combination of genre and stars; the results encouraged the firm to greenlight the series without requiring the makers to develop a pilot episode, which was a critical artistic criterion for the makers (Nocera 2016).

In addition to such secondary data-based approaches, concept testing can be employed. The history of concept testing in entertainment is a pretty troubled one, as Austin (1989) recalls. But we argue that the reputation of concept testing has been damaged mostly by the insensitive way it has been handled by entertainment managers, who often do not address the inherent tension between audiences' reactions to a new product and the involved artists' vision for it. Gitlin (1983) points out that estimates based on concept testing rely heavily on a mix of expertise and data. This mix requires responsible handling—we have noted simply too many anecdotes in which executives instead misused the approach to support previously held preferences (i.e., to support the launch of a favored film or the "killing" of another).

Our book gives evidence of the many product characteristics that exert a causal influence on entertainment product success, and concept tests should find ways to anticipate these factors' impacts on target audiences before those audiences have actually experienced the final product. We have stressed that entertainment success contains a marketability and a playability element, and concept testing should be particularly effective for the marketability element of success that so strongly shapes product diffusion patterns.

We concede, however, that running predictions at such an early stage faces major challenges. Probably the most serious one is that not much information is yet available about the product, and entertainment products evolve dramatically, over time, as they are developed. At this stage, predictions also require a particularly careful framing of and sensitivity regarding what to do with the prediction results. We have shown that early predictions, although being far from arbitrary, are error-prone, and decisions must acknowledge this high uncertainty. Using them in the wrong (i.e., deterministic) way can threaten creativity, turning artists against the firm and its managers. At the same time, when used in a sensitive way, early predictions can help managers to position a project better, anticipating audience reactions and allocating adequate funds. This is when everyone involved still has the chance to fundamentally modify the product and rework the strategy—including its artistic vision, as our previous discussion of the strategies of successful entertainment innovators such as Pixar has demonstrated.

Later-Stage Predictions for Entertainment Products

When the development of the product advances, additional information can be added to prediction models, and new prediction methods become available. When the product moves from concept to reality, prediction models can be used (1) to help a firm with a decision of whether or not to buy a product being made by others, or (2) with the aim of fine-tuning the final formulation of a product being developed in-house in order to optimize its eventual market performance.

Except for the product's actual performance, almost all factors we discuss in this book can be included in later-stage predictions, ranging from product factors, such as content and age rating, to advertising spending. Also available are distribution decisions and consumers' reactions to the product so far, as expressed in pre-release buzz and pre-orders.[269] Regarding the latter, Moe and Fader (2002) show for 66 albums that were released in 1997–1998 that such weekly pre-release ordering data can help to make more accurate predictions of post-release sales.

We have shown that the accuracy of such later models can be substantially higher than those which are run early; however, this gain in accuracy comes at a price. We have demonstrated that creative decisions usually have path dependencies—they cannot be easily altered in later stages of the development process. Also, contracts with distributors and decisions within the producing firm may prevent the making of major changes at this point. And the vast amount of data available at this point in time increases the tendency of basing decisions on the results in a superficial way, purely optimizing fit measures and treating correlations as causal effects.

Again, primary data from product tests can be collected at this stage and used for predictive purposes, such as by fitting audience reactions to a diffusion pattern. In such product tests, consumers are usually provided with the (nearly) completed product or parts of it, with the idea being that their reactions can help the team make final editing and positioning tweaks (DeVault

[269]Please see our discussion of the crucial role of buzz in today's entertainment marketplace in our chapter on earned entertainment communication.

2016; Marich 2013). For example, Avirgan (2015) describes how test marketing with a representative sample of potential viewers predicted the box office problems of the remake of the Marvel Entertainment film, Fantastic Four. But it also shows that such later tests might lack the ability to address the true causes of the problem; it was just too late in development to make the needed cast changes, so promotional activities were altered to cut the studio's losses.

One promising way to improve tests is to employ methods that do not rely solely on asking questions of test audiences, but instead infer audience members' reactions to concepts or product elements from measures of their bodily responses. Marketing scholars have been experimenting with biometric markers via techniques such as fMRI (functional magnetic resonance imaging) brain scans, eye-tracking, pulse rate measures, etc. In a specific approach, researchers from Disney have used infrared cameras and motion-capture technologies to measure the facial/body language of movie audiences to determine moviegoers' emotional reactions to specific scenes (i.e., smiling, laughing, or neither of the two) for nine Disney movies from 2015 to 2016 (Deng et al. 2017). By combining primary observations with technology and insights derived from large databases, such approaches might breathe new life into the under-used method of product testing for entertainment products.

An example for the power of combining multiple data sources for later-stage entertainment predictions is Eliashberg et al.'s (2000) MOVIEMOD approach. MOVIEMOD employs a diffusion model that is developed before a movie's release to forecast consumer awareness and adoption intentions for the movie and, subsequently, its success. MOVIEMOD uses a large set of the success drivers we discuss in this book ("features")[270] and derives audience reactions from a three-hour consumer "clinic," in which consumers are asked to fill out questionnaires, while some actually watch the movie in question. Based on this information, the authors classify consumers into certain stages (from "undecided" to "negative spreader") and statistically model consumers' transitions between stages, based on the number of people that are already in a certain stage. When the scholars implemented the approach in a real-word setting (for the film Shadow Conspiracy), they report that their predictions had an impressive prediction

[270]In the case of MOVIEMOD, the variables range from product variables (such as the quality, theme, story, and cast) to advertising and distribution.

error of only 4%, which also outperformed other prediction approaches they used as comparison standards.

Our previous discussion has shown that prediction models can strongly benefit from the inclusion of a product's initial sales; the combination of diffusion-based models and actual sales makes a great team. This is particularly relevant for products whose financial viability is less determined by short-term results, but their long-term performance, such as those for which the "niche concept" of marketing is used. One way to make full use of the post-release period is to measure the actual word of mouth for a product by those consumers who have already experienced it.[271] In line with our later analysis of word of mouth as a substantial influencer of entertainment product success, Dellarocas et al. (2007) prediction study shows that a diffusion model with word-of-mouth information forecasts the success of 80 movies (from 2002) better than one without.[272]

Multi-Stage Prediction Models

Finally, some *Entertainment Science* scholars have made the differing availability of information over the innovation process and its life cycle the very topic of their efforts. They have developed multi-stage models which enable managers to predict the performance of an entertainment product at different points in time.

One of these achievements is the model by Neelamegham and Chintagunta (1999), which predicts opening-week movie performance in the U.S. and in international markets at different stages, ranging from the concept stage, to the pre-release stage, to an international release stage (in which the film's domestic box office is included as predictor variable).[273] Using an MCMC estimation procedure, the scholars calibrated their model for 25 movies that had been released in the U.S. and one or more of 13 other countries in 1994–1996; ten others were used as holdouts.

Their results demonstrate that the prediction error decreases as more information becomes available; for example, the RMSE for the U.S. opening

[271]Please note that we make a clear distinction between experience-based word of mouth and other kinds of (speculative) consumer articulations.

[272]Let us note that Dellarocas et al.'s study measures only the *amount* of word of mouth and only compares the word-of-mouth model with one that does include neither word of mouth nor sales data.

[273]At the time Neelamegham and Chintagunta developed their model, sequential international releases were dominant in film. Please see also our discussion of such "intermarket success-breed-success effects" in the context of entertainment distribution decisions.

decreases by 24% when moving from concept to pre-release stage. And for the international opening performance, the RMSE declined across all 13 countries and the ten holdout films by 14% from the concept stage to the post-domestic stage (i.e., when information about a movie's U.S. performance is used). The improvement reached 20% when information on the film's local distribution is also included in the model. This shows the benefit of waiting to determine the value of the rights of a movie until such information becomes available.

In our own study of TV rights of films, we also applied a multi-stage prediction approach, but took the perspective of an international TV broadcaster (Hennig-Thurau et al. 2013). Using partial least squares for making rating predictions, we estimated a separate set of equations for a total of five stages, each time incorporating only the information available at that point in time for a broadcaster to use to predict the future TV ratings for a film. From a baseline model (which did not include *any* movie-specific information) to a model that includes a film's success in the foreign country's theaters, the prediction error (measured here as the RMSE[274]) shrank by 31%, while the explained variance increased by 34%. Figure 10.8 shows the changes in prediction error and variance explanation across the different stages.

In addition to RMSE and explained variance, the figure also illustrates the impact that such improvement in predictive power can have for the estimated monetary value of an example film for the TV station. We used Sony's Spider-Man movie and calculated the value of the film for the TV station based on the actual advertising fees per million viewers around the time we conducted the study. As can be seen in the figure, the value does not necessarily always increase—the change in valuation depends on the added information in each phase, and in this case the German box office did not meet the lofty expectations raised by the film's immense North American box office performance.

So, Better to Wait for the Fanny to Squirm or Use Prediction Models?

In this final section of our chapter on entertainment innovation, we have provided you with an overview of prediction models, illustrating the value of several specific models that have shown promise in aiding entertainment

[274] In the article, we refer to the standard error of the (regression) estimate, or SEE, which is mathematically the same as the RMSE.

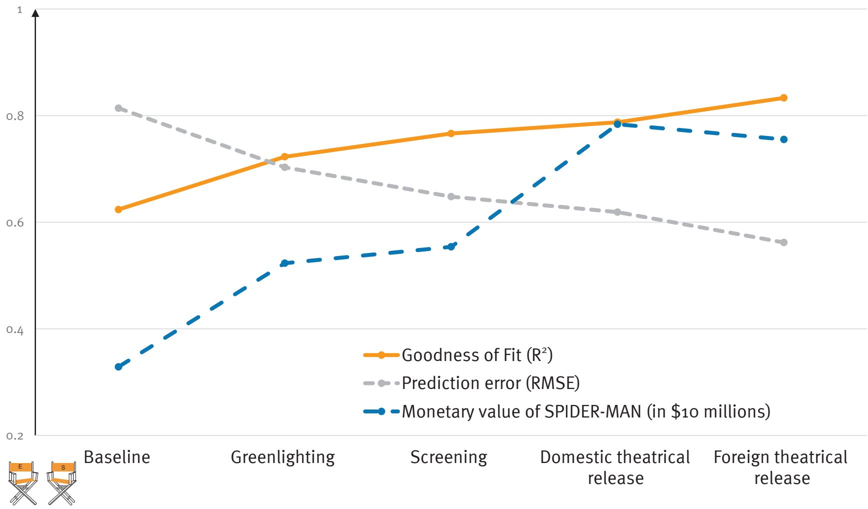

Fig. 10.8 Development of prediction accuracy over different innovation stages
Notes: Authors' own illustration based on results reported in Hennig-Thurau et al. (2013). The baseline model describes a model in which no film-specific variables are considered in the prediction. Film title is trademarked.

managers making tough innovation decisions. Despite the imperfections of any given model, the predictions provided by the modeling of data will improve the quality of decision making. Managers should not rely blindly on model-based predictions. But the other extreme—making "100 million-dollar decisions" based on "gut" (STX Entertainment's CEO Fogelson, quoted in Friend 2016)—is a ditch that needs to be avoided.

The insights that emerge from analytics can complement a manager's personal experience and increase his or her odds of making the right decisions at each stage of the product development process. The quality of prediction is connected to the types and amounts of data that are used, the statistical methods employed, and, last but not least, the theoretical model that underlies the estimations. But the most challenging part is something else: it's the development of a mind-set that integrates prediction results into decision making. The first half of this chapter provides guidelines on how to master that challenge.

And which of the several prediction models we have covered is best-suited? Certainly the specific conditions of the situation, such as the intended contributions of using prediction models, matter for this decision, but so do the resources a firm has at hand and the economic importance of the innovation(s) whose performance is to be predicted. Please keep in mind that all the models we cited are based on what was known about entertainment success drivers at the time of their creation. Our book offers an updated perspective of what influences product success in entertainment, and we recommend that entertainment managers include as many relevant features as possible and link them with product success in a way that is in line with state-of-the-art knowledge about the theoretical mechanisms and linkages.

There is one more thing we would like to ask you for. Please be careful if someone boasts that they can make predictions for you which are just "too good" to be true. Such approaches should be examined *very* carefully, paying attention to the conceptual foundation on which they are based, whether they purport to explain or to only predict, and the quality of the procedures used to select the sample of focal cases and to collect data. If such "behind-the-curtain" information is not offered, it might be better to let the offer pass.

Concluding Comments

In this chapter, we worked through state-of-the-art findings from organizational science and prediction research and applied them to the management of innovation in entertainment firms. By considering the unique characteristics of entertainment products and markets, we believe these are useful insights for entertainment managers, addressing the pressing challenge to innovate new entertainment products on a continuous basis.

In entertainment, those with artistic visions often consider bowing to commercial considerations as sullying—or even defiling—the actual work of art. Finding a way to respectfully balance artistic and economic goals is the foundation for the entire chapter. Our analysis showed that this can only be achieved by creating a culture that combines autonomy and responsibility, along with an organizational structure that attracts people with the right skills and values and equips and enables them to be creative, but with discipline.

We complemented this firm-level analysis of factors that contribute to prolific innovation activities with a product-level analysis of approaches that can be used to improve managers' understanding of a new product's commercial potential. We reviewed the different econometric prediction methods that are available for such a purpose and discuss concrete scientific models that have been developed for predicting new product success at different stages of the innovation process. No approach is perfect, but used thoughtfully, predictions can be generated that will provide valuable input into key managerial decisions.

Whereas the decisions we discussed in our four product episodes are essential for entertainment managers, having the right product is only one part of a complex equation for success. We now move on to the second "P" of the entertainment marketing mix: promotion. Specifically, we examine the rich repertoire of tools that firms can use for communicating with consumers (or to get consumers to communicate with each other) regarding an entertainment product, along with other, less controllable information sources such as success cascades, word of mouth, and expert reviews.

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