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Lessons Learned from Two Decades of Anticancer Drugs

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Tremendous efforts have been made to elucidate the basis of cancer biology with the aim of promoting anticancer drug development. Especially in the past twenty years, anticancer drug development has developed from conventional cytotoxic agents to target-based and immune-related therapies. Consequently, more than 200 anticancer drugs are available on the market. However, anticancer drug development still suffers high attrition in the later phases of clinical development and is considered to be a difficult and risky therapeutic category within the drug development arena. The disappointing performance of investigational anticancer candidates implies that there are some shortcomings in the translation of preclinical in vitro and in vivo models to humans, and that heterogeneity in the patient population presents a significant challenge. Here, we summarize both successful and failed experiences in anticancer development during the past 20 years and help identify why the paradigm may be suboptimal. We also offer potential strategies for improvement.

Current progress of anticancer drug development

Cancer, which is characterized by uncontrolled growth of cells in the body, is one of the most difficult and complex diseases to treat [1-3]. Cancer patients suffer high mortality rates, which range from 1.1% for prostate cancer to 92.3% for pancreatic cancer within five years after cancer diagnosis. Therefore, anticancer drug research and development (R&D) is a challenging and daunting activity, and the likelihood of failure is high [4]. Fewer than 5% of developed anticancer compounds reach the market [5]. Furthermore, compared to other therapeutic categories such as cardiovascular disease and arthritis, an anticancer drug has approximately one-third to one-half greater failure rate per attempt [5, 6]. Although there are a lot of difficulties and barriers in anticancer drug development, drug makers are still pursuing opportunities for anticancer drug candidates due to their high cost-benefit rate [7, 8]. For example, oncology is ranked in the top therapeutic class by global sales which amounted to 78.94 billion US dollars in 2015.

Approved anticancer drugs

The ultimate task for an anticancer drug is to kill the tumor cells and/or control proliferation of tumor cells to prolong patient survival and improve their quality of life. However, there are many different mechanisms by which this can be achieved. Based on the key biochemical mechanism of anticancer action, anticancer drugs can be categorized as: (i) *nucleic acid biosynthesis blocker*; (ii) *the structure and function of DNA interferer*; (iii) *transcription interferer and RNA synthesis blocker*; (iv) *protein synthesis and function interferer*; (v) *hormone homeostasis influencer*; (vi) *immune system modulators*. Consequently, drug makers have produced four major groups of anticancer drugs including cytotoxic drugs (alkylating agents, antimetabolites, antibiotics, plant extracts, and miscellaneous cytotoxic drugs), targeted-based agents (e.g. bevacizumab), hormones and hormones antagonists (e.g. tamoxifen), and immunomodulators (e.g. nivolumab). From the classic “Seed and soil hypothesis” that first described metastasis [9] to the first description of “immune-based cancer therapy” [10], every milestone made in the cancer field has driven a wave of anticancer drug development [11] (**Figure 1**). In the past two decades, anticancer drug development has moved on from conventional non-specific cytotoxic agents which often kill proliferating normal cells as well as tumor cells [12, 13]. In the place of cytotoxic agents, there is a focus on specific target-based cancer therapy [14] designed to hit tumor cells only, and on immune-related modulators that help the patient’s immune system to defeat tumor cells [10, 15, 16]. Furthermore, a series of regulations, initiatives, and guidance have been developed to facilitate anticancer drug development [17, 18].

According to the USA National Cancer Institute drug repository, there are a total of 227 approved anticancer drugs (Supplementary **Table S1**) to treat about 40 different types of cancers. There are multiple drug options developed for leukemia, non-Hodgkin lymphoma and breast cancers. In contrast, for some cancer types such as penile or liver cancer, there is only one drug treatment available. On average, available anticancer drugs are used to treat 3.44 cancer types. For example, nivolumab (Opdivo[®]) is a monoclonal antibody that works as a checkpoint inhibitor by inhibiting the programmed cell death receptor 1 (PD-1), which is

overexpressed on diverse of tumor cells and is in charge of down-regulating the immune system and suppressing T cell inflammatory activity. Activated PD-1 blocks T-cell activation and aids the tumor in escaping immune detection. By blocking this PD-1 activation, nivolumab aids the immune system in attacking the tumor cells [19, 20]. Nivolumab was initially approved as a first-line anticancer drug to treat advanced melanoma in 2014. In 2015, the indication of nivolumab was expanded to squamous cell lung cancer and as a second line anticancer drug to treat renal cell carcinoma . In addition, nivolumab was also approved in 2016 to treat classical Hodgkin lymphoma (cHL) in patients who have relapsed or progressed after post-transplantation brentuximab vedotin and autologous hematopoietic stem cell transplantation (auto-HSCT) . In contrast, approximately 45% of rare diseases are rare oncological diseases [21], some of which have no treatment options available on the market [22]. There is no obvious correlation between the number of drugs to treat a particular cancer and the five-year survival rate/estimated new cases for different cancer types, which may imply that developments in treatment is mainly based on the understanding of cancer nature history and on our accumulated knowledge on pathogenesis and etiology of cancer (**Figure 2**).

Clinical trials related cancers and other neoplasms

Anticancer drug development remains a major focus of clinical trials and approximately 40% of studies in clinicaltrial.gov are relevant to the condition “*Cancers and Other Neoplasms*” [23]. These clinical studies are widely sponsored by drug makers, academic researchers, and federal governments. For example, the NCI has supported or sponsored a total of more than 5000 cancer-related clinical trials. Among 5154 cancer-related clinical trials, about 73% (3735/5114) of clinical studies are aimed at developing treatment options for cancers. These cancer treatment-related studies are in different clinical phases with 45% in phase I, 53% in Phase II, 8.6% in Phase III and only 0.6% in Phase IV. This shows that although many compounds enter the early phases (I & II), relatively few make it to Phase III or beyond.

High failure rate of anticancer drugs

Ongoing efforts have uncovered cancer genetics, novel therapeutic targets, and clinical biomarkers related to survival rate, which have led to better understanding of the molecular basis of cancer. However, it seems that our ability to translate these research findings into more effective clinical cancer treatments is still remarkably limited [24, 25]. Many factors are responsible for a high attrition rate of anticancer drug development at each phase from preclinical to post-marketing of drug development.

***In vitro* assay approaches**

The key challenge for preclinical *in vitro* and *in vivo* tools such as cancer-cell-lines and animal models is whether they can be used to make reliable “go/no go” decisions on which candidates to progress into the clinical phases. Concerns have been raised as to whether cancer-cell-line based assay systems can meaningfully reproduce the tumor cell behaviors in cancer patients. High-throughput screening (HTS) based *In vitro* assays have a lot of advantages since they can be used to conduct a rapid screen of anticancer drug candidates against different endpoints using different cancer cells [26, 27]. In the current preclinical setting of anticancer discovery, HTS *in vitro* assays together with combinatorial chemistry have become a standard tool to readily identify agents with clinical potential. *In vitro* assays have been widely applied in various cancer preclinical studies and diverse platforms such as NCI60 [28], LINCS project led by NIH [29], and anticancer drug sensitivity studies from both the Broad Institute [30] and the Wellcome Trust Sanger Institute [31].

There are two major types of *in vitro* assay approaches for anticancer drug discovery – phenotypic screening and target-based screening. Unlike the target-based approaches based on engineered cloned genes either in cell-based or biochemical *in vitro* assays, phenotypic screening assays have relatively straightforward endpoints for ameliorating the cancer phenotype, which are exemplified by selectively killing cancer cells, eliminating cancer cell proliferation or decreasing the cancer cell size [32]. There is some debate on which technology contributes more to discovery of first-in-class drugs [33, 34]. Based on FDA approved drugs statistics (1999 ~ 2008), phenotypic screening took more first-in-class drugs to the market than

target-based approaches. However, another much larger scale of studies based on from 1999 to 2013 drew an opposite conclusion that 78 of 113 FDA-approved first-in-class drugs are based on target-based approaches. In the anticancer drug area, target-based approaches introduced more anticancer drugs to the market [35], but both types of screening have their own values and can lead to viable drugs [37, 41]. The target-based screening approach is hypothesis-driven, in which cancer disease modeling and pathway analysis leads to a candidate protein or proteins. Compounds that perturb or interfere with the candidate protein are considered as lead compounds. The target-based approaches have had a lot of success, especially in kinase inhibitors [36]. Between 1999 and 2013, 21 of 31 oncology new molecule entities (NMEs) discovered by target-based approaches are kinase inhibitors [32]. However, the target identification and validation for anticancer drug development is of great challenge. First, validated anticancer drug targets are far more difficult to identify than we expected. Candidate anticancer targets are initially identified from different biological based HTS efforts, which is mainly hypothesis-driven. Therefore, further in-depth validation experiments are needed to establish that the proposed candidate targets have desired therapeutic effects and low risk [37]. There are fewer than 100 anticancer targets implicated in FDA-approved anticancer drugs, which is still a small proportion compared to the 20,000 human genes that encode approximately 500,000 proteins in the human genome [38, 39]. Furthermore, due to the limited and incomplete knowledge of cancer-related proteins involved in specific human malignancies, even drug candidates with high potency identified in the screening process may have little or no value. For example, colorectal tumors harboring a KRAS mutation that activate the EGFR protein signaling pathway fail to respond to EGFR inhibitors such as cetuximab (*Erbitux*) in mutated KRAS-related colorectal patients [40]. Also, some cancer-related tumor-suppressor genes such as RAS are not directly “druggable”, which creates another hurdle to apply target-based screen approaches [41, 42]. For example, the GTPases were identified as the key enzymes to activate RAS protein. Therefore, efforts were made to inhibit GTPases to control RAS activation. However, the low molar affinity between small molecules and GTPases made inhibiting GTPases untenable. Furthermore, RAS protein function is highly associated with the inner face of the plasma membrane, further complicating controlling RAS activation, since small

molecules could not reach the RAS protein. [43]. Some advanced cell-based assay technologies including 3D *in vitro* assay models [44], organ-on-a-chip systems [45-47], cellular imaging [48, 49], and iPSC stem cells [50] may improve the performance of target-based *in vitro* assay performance. For instance, the multicellular co-culture system mimics the tumor microenvironment by migrating tumor cells to adjunct microenvironment cell types such as endothelial cells and fibroblasts, thereby modeling the complex pathological features of different cancer types. This strategy has been applied for drug efficacy screening for breast cancer [51].

Meanwhile, phenotypic based screening seems to be experiencing a resurgence in anticancer drug discovery [52, 53]. Phenotypic *in vitro* screening is considered as a semi-empirical approach that does not require knowledge of the underlying mode of action and molecular mechanisms of the compounds being evaluated. Cancer phenotypes can be observed in cell lines, and thus compounds that disrupt that phenotype may be viable drugs. In particular, human primary cells, immortalized primary cells, and iSPCs have been widely applied to the phenotypic screening assays, which has provided a lot of success in anticancer drug discovery [34]. One example is carfilzomib, which is a selective proteasome inhibitor used to treat multiple myeloma after the patients received prior therapies such as bortezomib and lenalidomide. Proteasome inhibitors could induce apoptosis and inhibited tumor growth. Carfilzomib could reversibly bind to the chymotrypsin-like (ChT-L) active sites in the 20S proteasome, which potently control the cell growth and proliferation. The efficacy of carfilzomib was originally discovered by using a cytotoxicity screen [54]. One difficulty of the phenotypic screening approach is dosage optimization since there is no clear target for the cancer types. Other challenges include optimising chemistry against an unknown target and prediction of unwanted toxicities that may normally be elucidated from target distribution.

Besides considerations regarding the biological nature of cell-based assays for anticancer drug discovery, the quality of HTS assays and how to interpret the results also play a role in better harnessing the technology. One example is the inconsistency in two large drug response data sets from the Cancer Cell line Encyclopedia (CCLE) [30] and the Genomics of Drug Sensitivity in

Cancer [31] based on cell-based HTS assays [55]. There are 15 common drugs characterized in 431 cancer cell lines between the two studies, which showed a substantial divergence in drug response, although the gene expression similarity is well-established [55, 56]. There are a lot of underlying reasons contributing to the divergence. The batch effect of fetal bovine serum used in the different studies, the mathematical equation employed in curve-fitting of concentration-response curves, and even the coating on plastic wells may be influential. Another potential influence on this divergence is which measure, quantitative or qualitative, should be used as the assay endpoint. For example, the method employed to measure the metabolic activity by assessing levels of the energy transfer molecule ATP, could influence the assay's endpoint, contributing to the observed divergence. Due to these concerns, *in vitro* assay results should not be interpreted as a pure statistical measurement, but rather interpreted in the context of the generated hypotheses that each drug was tested under. [57]. Undoubtedly, the reproducibility of cell-based screening assays for anticancer drug development is of great importance [58, 59]. Considering cell-based assays are plagued with the concerns of false positive and false negatives [60], the statistical practices [61] and application domain of assays [62] need to be standardized and defined [63]. Wassermann *et. al.* [64] revisited the screening collection that never showed biological activity based on HTS techniques, and therefore became defined as 'dark chemical matter' (DCM). It was found that some of the false negative compounds based on HTS screening did show biological relevance under the quality control assays such as prospective reporter-gene assay gene expression experiments. Therefore, critical data quality control and wise design of experiments is a "must" to ensure reproducible and reliable results generated from cell-based assays [65].

Animal models

Animal models are widely used to verify the biological relevance of the identified target for tumor response, to predict the first-in-human (FIH) dose and maximum tolerated dose (MTD), to determine the potency of anticancer drug exposure target, and to detect the qualified pre-clinical prognosis, diagnosis and predictive biomarkers [66, 67]. The principle behind animal

211 models is that the physiological features of animals closely resemble humans in genetic,
212 epigenetic, and environmental factors, which is open to debate.

213 The lessons learned from animal models in anticancer drug development are mainly related to
214 how animal models could better resemble cancer pathophysiology in humans. The challenges in
215 extrapolation from animal studies to humans for anticancer drug development may be not only
216 attributed to the technical and biological transferability of the animal model itself but may also
217 involve the design, execution, and interpretation of the results from animal models [68]. Below
218 we explore lessons learned on how to improve the animal model performance such as animal
219 model application, and PK/PD model optimization (**Figure 3**).

220 *Application domain of animal models*

221 Various cancer animal models have been developed to mimic patient tumors, including human
222 cancer cell-line based xenograft models [69], patient-derived xenografts (PDXs) [70-72],
223 immune-competent models [73], and genetically engineered mice (GEM) [74]. The pros and
224 cons of different kinds of animal models for anticancer drug development have been intensively
225 discussed [66, 75-77]. The human cell-line based xenograft model was established by using the
226 mouse as an immune-deficient host for transplanted human cancer cell-line growth. The classic
227 example of human cancer cell-line based xenograft model is so called athymic 'nude
228 mouse'[69]. The transplanted human cancer cell-line model is easily tractable, controlled and
229 experimentally convenient. However, there are also some shortcomings of this cell-line based
230 xenograft models. First, the nude animal is immune-deficient, which does not resemble the
231 immune environment of human tumors. Therefore, the human cell-line based xenograft models
232 are not applicable for immune-related anticancer drug development. Second, because cell lines
233 adapt through the clonal selection process as they grow on plastic, they do not repeat the
234 genetic diversity seen in human tumors, nor do the cell lines reflect intratumoral heterogeneity.
235 Additionally, the human cancer cell line is typically extracted from early-stage cancer patients.
236 Finally, the subcutaneous location may not foster important tissue-specific stromal infiltration,
237 which means the model is a poor fit for soft tissue sarcomas with typical tumor growth. Due to

these limitations, some reports suggest combining the different human cell line types in xenograft models may improve the performance, which has been successfully for ER+ and triple-negative breast cancers[78]. The human PDX model, which directly implants the human tumors into a mouse, has been widely applied in both academia and industry for anticancer drug development [79, 80]. The PDXs suffer similar concerns as the human cancer cell-line based xenografts regarding to lack of immune features and difficulty of tumor growth in subcutaneous regions. However, the PDXs could better replicate the mutational heterogeneity and reflect the intricacies of tumor subpopulations [81]. For example, some mutation-related cancer subtypes such as mutated ESR1 related ER+ breast cancer could be identified only in the PDX model but did not show any signal in cell-based xenograft [82]. One of the big concerns of animal models is how to mimic the immune-comprised systems of cancer patients in the mice. The immune-competent models and genetically engineered mice (GEM) successfully reproduce the immune features and tumor interaction in animals by employing different bioengineering techniques [83]. The immune-competent model is established by transplanting mouse cell line and tumor tissues to the immune-competent host with immune cells and fibroblast incorporated. The immune-competent models provide interactive immune system features and mimic tumor microenvironment, thus more closely approximating human cancers. However, the limited available cell lines for immune-component models coupled with rapid and uncontrolled cell growth limit its wide application[66]. The GEM model aims to manipulate the mouse genome to introduce the germline mutation or conditional mutations for different tumor types. Especially with the rapid development of gene editing technology, the GEM model has a promising future for cancer etiology, epigenomics and personalized cancer treatment [74]. One promising example of application of the GEM model for anticancer development is selumetinib (clinical Phase I/II/III), which is designed for multiple cancer types including triple-negative breast cancer [84], non-squamous cell lung cancer [85], pancreatic cancer [86], and neurofibroma [87, 88]. One of the indications is KRAS-mutant non-small cell lung cancer (NSCLC). A co-clinical trial that combines preclinical and clinical models was employed to observe the drug response (selumetinib and docetaxel) for NSCLC in humans and in genetically engineered mice and found the selumetinib could significantly increase the efficacy of

docetaxel, a standard chemotherapy [85]. Meanwhile, there are also many cases of failure of animal models in anticancer drug development (**Table 1**).

No single animal model will fit all purposes. For example, the cell-based xenografts and human PDXs models are more suitable for tumor-cell-derived signal detection such as cell death and proliferation but not fit for immune-related anticancer drug discovery. GEM models and immune-component models may not be useful for intratumoral subclonal identification due to limited types of mutations and technical hurdles for monitoring internal organs[89]. A combination of animal models and cell based *in vitro* assays could provide more robust results. Furthermore, some novel animal models such as the 3D organoids based cell-line xenografts may also offer alternative means to further update and improve animal model performances[90].

PK/PD model optimization

Anticancer drugs are considered as one of the most toxic drug classes in the therapeutic spectrum [12, 91, 92]. Associated adverse drug reactions cover almost every organ system and are known to cause multiple organ toxicities, which could be explained by the nature of anticancer drugs which are intended to kill cells together with their tendency to off-target promiscuity [93]. A major difficulty is the unexpected side effects observed in the clinical phase that could not be detected in animal models, and *vice versa*. Dose is the key factor to balance the efficacy and safety profiles for anticancer drugs [94-96]. Due to the anticipated toxicities, Phase I clinical trials are often conducted in cancer patients under The International Council for Harmonisation of Technical Requirements for Pharmaceuticals for Human Use (ICH)S9 . However, for some less toxic anticancer therapies such as targeted therapies, Phase 1 trials may be conducted in volunteers under ICH M3. For these latter trials, one of the most important tasks for animal models is to establish the maximum recommended starting dose (MRSD) for clinical Phase I study for healthy human volunteers. The FDA has developed guidelines for the industry such as “*Guidance for Industry Estimating the Maximum Safe Starting Dose in Initial Clinical Trials for Therapeutics in Adult Healthy Volunteers*”. The conventional MRSD dose

prediction strategies are based on no observed adverse effect level (NOAEL) [97] and the minimum anticipated biological effect level (MABEL) [98] approaches and have been widely applied to first-in-human (FIH) dose estimation. Currently, the FIH dose is typically calculated by using one tenth of the toxic dose in 10% of the animals (STD10), which is the dose that causes severe toxicity in 10% of rodents [99]. Typically, at least two species are required in toxicological studies: one rodent such as the rat or mouse) and one nonrodent such as the dog, minipig or monkey.

PK/PD models play an increasingly important role in preclinical studies [100]. Since anticancer drugs often have a very narrow therapeutic index (TI), a more precise PK/PD model is required to estimate the FIH dose. Novel PK/PD models tends to combine diverse properties including pharmacology (potency, selectivity), preclinical safety profiles (doses and exposure related to toxicity), risk assessment (target and chemical assessment) and surrogate biomarkers such as those related to clinical and toxicity endpoints into the same framework to better predict the FIH dose [101-104]. One recent example added a pharmacogenomics dimension to the PK/PD model to define equivalent PK/PD dosing regimens for different genetically distinct tumor models [105]. Such a concept has been successfully used to define the FIH dose of epidermal growth factor receptor (EGFR) inhibitors such as gefitinib for different EGFR mutation carrier groups [106].

Preclinical models may perform well and effectively, but only when the context is well -defined and data are interpreted with care. To reproduce successful cases and apply valuable experience into anticancer drug preclinical practice, the comprehensive and critical re-evaluation of cell-based and animal models is essential. Some of the large-scale consortium efforts and available public datasets make it possible to conduct meaningful retrospective analyses of quality control suitability of the disease context and the utility of preclinical anticancer tools [107-109]. Furthermore, some alternative approaches such as the Phase 0 clinical trial may be a promising complementary tool in pre-clinical anticancer models [110-112]. A phase 0 clinical trial is conducted prior to the conventional clinical phase I dose escalation, tolerability assessment, and safety evaluation with limited human expose (usually

10-15 patients) and short period (typically with one week) and aims to optimize the PK/PD features especially oral bioavailability and half-life of anticancer drugs.

Divergence between Clinical Phase II and Phase III

According to statistics of Clinical Development Success Rates between 2006-2015 (<https://www.bio.org/sites/default/files/Clinical%20Development%20Success%20Rates%202006-2015%20-%20BIO,%20Biomedtracker,%20Amplion%202016.pdf>), anticancer drug development suffers a higher failure rate (75.4%) from clinical Phase II to Phase III when compared to non-oncology drugs (65.7%). The FDA recently published a report entitled “22 Case Studies Where Phase 2 and Phase 3 Trials Had Divergent Results” (<http://www.fda.gov/aboutfda/reportsmanualsforms/reports/ucm535541.htm>). Among the 22 cases, five drugs (5/22=22.7%) are oncological agents (see **Table 2**). The major reason for anticancer drug failure from clinical Phase II to Phase III is lack of efficacy [113, 114]. Improvement of survival rate in patients is considered as the gold standard for anticancer drugs in clinical trial. Clinical endpoints such as overall survival (OS), disease-free survival (DFS), progress-free (PFS), time to progression (TTP) are also widely applied in cancer clinical studies.

One of the difficult lessons from the past few decades of anticancer drug development is that positive results in Phase II do not guarantee a subsequent success in Phase III. This could be because the limited patient population in Phase II trials may not accurately reflect the broader patient population in Phase III trials. Furthermore, clinical endpoints in Phase II may be related to controlling signs of disease over the short-term such as PFS which is easier to achieve than the desired clinical endpoint for success in Phase III, which is lengthening lifespan. Thus, these two endpoints may not correlate. In addition, the statistical measure in the smaller Phase II population may suffer from over-fitting, in which the benefits ascribed to the drug treatment are actually the result of random noise, and thus do not translate into larger populations. Specifically, the statistical model may outperform within the context of Phase II but not within

the extended patient population in the clinical Phase III. Alternatively, there may be simple bias which is less likely to occur in the larger patient population in Phase III.

Elimination of the divergence between Phase II (“therapeutic exploratory”) and Phase III (“therapeutic confirmatory”) is the key to improving successful rates for anticancer drug development. Patient recruitment in the late-stage clinical trials has been a great stumbling block. Around 20% of cancer clinical trials were never finished due to insufficient patient enrollment, which is largely attributed to uncertain benefit to the cancer patients participating in the trials [115]. In addition, more sensitive surrogate biomarkers are needed for use in the clinical trials. Patient recruitment in a clinical trial is mainly based on the pathology and morphology of diseases, which aims to collect homogeneous populations. However, patients collected in Phase III are substantially genetically heterogeneous [116]. For instance, the patients may carry different genetic mutations that are related to wholly different cancer subtypes, and therefore the compound under evaluation may have widely varied effects on these diverse tumors. With the advances in high-throughput “omics” techniques, it is possible to collect more information on patients such as genetic background and epigenetic properties to facilitate patient recruitment in Phase III.

The divergence among the population does not just exist in different clinical trial phases but also manifests in the post-marketing stage. One example is bevacizumab (Avastin®). Bevacizumab, a vascular endothelial growth factor (VEGF) inhibitor, is the best-selling anticancer drug in the world, which was approved to treat multiple cancers such as colon cancer, lung cancer, and glioblastoma. In 2008, bevacizumab was approved by the FDA to treat metastatic breast cancer. However, this approval was revoked by FDA due to hypertension and kidney toxicity and poor progression-free survival profiles from post-marketing studies [117]. Another example is ponatinib, a BCR-ABL tyrosine kinase inhibitor (TKI). In clinical Phase II studies of ponatinib, there were a total of 449 patients involved. Among the 449 patients, only the 128 patients carrying the T351I mutations in BCR-ABL had a positive response to the treatment. However, ponatinib was given fast-track approval by the FDA on the basis of these Phase II results, and as such, was approved for chronic myeloid leukemia (CML) for the general

population in December 2012. Then, some published results the following year reported incidents of severe cardiovascular toxicity in patients taking ponatinib, causing the FDA to suspend approval of the drug. Just seven weeks later, the FDA provided guidance to reintroduce ponatinib back to the U.S. market for a more specific patient group (T351I mutation carriers) with CML [118]. These two examples highlight the divergence between the clinical study and general population groups and its consequence to the anticancer drug approval process, which also stimulates us to rethink the current clinical design of anticancer drug trials. First, the current clinical endpoints for anticancer drugs are focused on the time-to-event type, which creates a lot of problems when translated from one clinical phase to another due to both unclear biological meaning and statistical measures. More effective biomarkers relevant to cancer pathology and drug pharmacology are urgently needed to improve the translation from one clinical trial to the next. Biomarkers that more accurately reflect the efficacy and clinical benefits of anticancer treatment may improve performance of the compounds in clinical trials. Examples of possible biomarkers include circulating tumor DNA, concentration of antigen KI67 in the serum level, and circulating tumor cell (CTC) counts [117]. Secondly, the clear endpoints and desired target population should be fully taken into consideration in the design of clinical trials and patient recruitments. Specifically, the genetic background of recruited patients could be helpful to identify patients with specific genetic mutations most likely to benefit from the study drug. With the decreased cost (less than \$1,000) of sequencing techniques and advanced PCR assays, it is more possible to implement genetic testing as part of clinical trials.

Anticancer drug resistance

One of the chief lessons that has emerged in the past two decades of anticancer drug development is that the promise of targeted therapy is tempered by the realities of drug resistance. Cancer drug resistance, in which the tumor cells are either inherently unresponsive to the treatment drug or develop changes that allow them to tolerate the drug, is one of the biggest challenges in anticancer drug development. Some known mechanisms that promote or induce anticancer drug resistance include drug transport and metabolism such as drug efflux and drug activation/inactivation, drug target alterations, DNA damage repair and downstream

404 resistance mechanisms such as deregulation of apoptosis and autophagy [119]. These
405 mechanisms are divided into two categories: intrinsic and acquired. Intrinsic resistance means
406 the resistant is pre-existing in the tumor cells before the chemotherapy. Acquired resistance
407 occurs in the cancer development process, which can involve sub-cloning of tumor somatic
408 mutations, increased target expression level and recruitment of alternative compensatory
409 signaling pathways [120]. Moreover, molecular and genetic heterogeneity present in tumors
410 contributes substantially to drug resistance [121].

411 Although diverse underlying mechanisms of anticancer drug resistance have been deciphered in
412 the past two decades, we still have a long road ahead before we have sufficient knowledge to
413 overcome this issue. [119]. Often tumors display multiple drug resistance (MDR), which is one
414 of the major reasons for ineffectiveness and toxicity of chemotherapeutic agents [122]. The
415 ATP-binding cassette (ABC) transporter family was identified as one of the causal factors for
416 MDR. There are a total of 49 ABC transporters. However, very few proteins such as MDR1,
417 MPR1, and BCRP have been studied and identified in relation to MDR [123]. Initial efforts to
418 develop ABC transporter inhibitors such as MDR1 inhibitors to overcome tumor resistance have
419 yielded disappointing clinical outcomes. The first generation of MDR inhibitors had low affinity
420 for ABC transporters, and increased dosing caused unexpected side effects [124]. The second
421 and third generation MDR inhibitors had improved pharmacological profiles with higher affinity
422 to ABC transporter. However, the clinical effectiveness is still suboptimal. For instance, the
423 MDR1 inhibitor tariquidar was proposed as an adjuvant against multidrug resistance in late-
424 stage breast cancer. However, the clinical trial (phase II) showed no benefit for patients'
425 survival[125]. The possible reason may be the functional redundancy within the ABC
426 transporter family or that other contributors, beyond ABC transporters, affect tumor resistance.
427 Some preclinical cell-based HTS screening panels have been developed for ABC transporter
428 screening, which could be important reference information in monitoring potential MDR [126].
429 Furthermore, rational drug combinations have been proposed to conquer MDR by targeting
430 multiple components of the cancer process to improve the efficacy and overcome tumor
431 resistance [127]. Research increasingly indicates that drug combinations that target multiple

pathways are more effective than targeting multiple targets within the same cancer-related pathway [119]. Tumors evolve over time in terms of their epigenetics, genetics and gene expression levels, which causes tumor initiation, metastasis, and drug resistance. Mutations that arise in the early stage tumors could further evolve into very different mutation types, which may cause the tumor to adapt and develop resistance to treatment. One example of evolving mutations is provided by gefitinib, which is an epidermal growth factor receptor (EGFR) inhibitor designed for non-small-cell lung cancer (NSCLC) treatment. Gefitinib is effective in patients with specific activating mutations in EGFR such as L858R in exon 21 but these benefits often last only for the first year of treatment. However, the evolving tumor acquires a new gatekeeper mutation named EGFR-T790M to maintain the genetic information and control the tumor growth, which cause 50% of patients to experience drug resistance and ultimately treatment failure [128]. In some cases, researchers have designed second-generation drugs that overcome the initial resistance. One example is the BCR-ABL1 oncogenic kinase inhibitors for chronic myeloid leukemia (CML). The first BCR-ABL1 inhibitor was effective but patients relapsed due to sub-cloning of the T315I mutation of BCR-ABL1. Drug makers developed the second generation of BCR-ABL1 inhibitors such as dasatinib and bosutinib against the T351I mutation in BCR-ABL1 [129].

With the wide spectrum of cancer drug resistance mechanisms, it seems unlikely that the dream of a “magic bullet” to cure cancer will ever be realized [119]. However, we should not lose sight of significant progress being made as anticancer drugs have become more precise and have prolonged and improved patients’ lives. With the assistance of modern omics techniques, we are experiencing a substantial increase in our ability to identify the molecular mechanisms for cancer drug resistance. Thus, the cumulative experience of cancer drug resistance research, from conventional chemotherapy to target-based therapies, can serve as the foundation to drive further research and to increase the number and effectiveness of anticancer drugs.

New trends for anticancer drug development

As novel technology is increasingly applied to the challenge of cancer, new opportunities are emerging to innovate in anticancer drug development. Here is a glimpse at some of the great strides including precision medicine, cancer stem cells, and drug repositioning (more in **Figure 4**).

Precision medicine

Precision medicine is an approach to integrate molecular and clinical information to better understand of disease by using novel genomics techniques such as next generation sequencing [18, 130]. Precision medicine aims to utilize the unique genetic profiles of patients to look for better treatment solution, which provides the right drug, the right dose to the right patients with reduced safety concern.

Targeted cancer therapy as an important practice of precision medicine is considered as an indispensable components of current anticancer drugs development [131]. Unlike the conventional chemotherapy, targeted cancer therapy works on the specific target in cancer-related molecular pathways to treat cancer. Targeted cancer agents are broadly divided into small molecules and monoclonal antibodies. The small molecule based targeted cancer agent is able to interact with the target inside the cell by penetrating the cell membrane, and monoclonal antibodies are designed to target specific antigen on the cell surface. For example, trastuzumab as a monoclonal antibody is designed to treat HER2 related breast cancer, which is only beneficial to the patients with HER2 protein overexpressed [132]. The precision medicine provides more deep resolution of genetic feature of cancer patients, which makes the patients with different genetic mutation as a group to receive the specific treatment option possible. The successful examples include imatinib for patients with chronic myeloid leukemia carrying a BCR-ABL mutation [133] and vemurafenib for those with melanoma or thyroid cancer who have the BRAF V600E variant [134]. The implementation of precision medicine requires the integration of molecular diagnosis into the anticancer drug discovery process [135]. Currently, there are approximately 35% (71/203) established pharmacogenomics biomarkers for approved anticancer drugs and incorporated into FDA-approved drug labeling .

The qualified biomarker or “fit-for-purpose” biomarker is the key to precision medicine practice [136]. Rich resources on genetic variants and their relationship in human cancers are available [137, 138]; however, understanding of how to leverage these findings into clinical practice (from the relationship, correlation to translation) is still suboptimal. Furthermore, there are some concerns over how many patients could actually benefit from precision medicine [139, 140]. One disappointing report on personalized cancer treatment based on genetic biomarkers found only 30% patients had a positive response to personalized cancer treatment strategy and this amounted to an average two-month improvement of progression-free survival [141]. As highlighted recently, in ‘precision medicine’ the word ‘precision’ is being used in a colloquial sense, to mean both ‘accurate’ and ‘precise’. Precision implies a high degree of certainty of an outcome but in fact, the opposite will probably result. The new tools for tailoring treatment will demand a greater tolerance of uncertainty, a greater ability to interpret ‘omics’ data and a greater facility for calculating and interpreting probabilities than we have been used to as physicians and patients [142, 143]. Furthermore, although the price of next generation sequencing for diagnosis is continually decreased, the expanse for development personalized medicine based on individual genetic characteristics is still huge. Therefore, more efforts should be encouraged to standardize precision medicine practice in both clinical translation and the regulatory setting [144, 145].

Cancer stem cells

The discovery of cancer stem cells (CSCs) in the late 1990s triggered intense research efforts into this specialized subpopulation of tumor cells. CSCs, also referred to as tumor-initiating cells (TICs) can self-renew and drive tumorigenesis [146, 147]. CSCs play an important role in cancer initiation [148, 149], maintenance [150, 151], metastasis [152] and recurrence[153-155]. Therefore, a lot of efforts have been made to decipher CSC function in cancer pathogenesis, and to apply these findings in anticancer drug development [156].

To date, CSCs have been discovered in multiple types of solid tumors such as breast cancer [157], lung cancer [158], and brain cancer [159]. Some targeting cellular surface markers

including *CD133* [160], *CD90* [161], *CD33* [162] and *PKA* [163], key pathways such as *Norch*, *Hedgehog*, *Wnt*, and *NF-κB* signaling pathways [164], and transporters including ATP-binding cassette (ABC) transporters [165] have been detected in CSCs. Studies have sought ways to specifically target CSCs. Fang *et. al.* [166] performed HTS screening of small molecules and found LF3 (a 4-thioureido-benzenesulfonamide derivative) could effectively block the self-renewal of cancer stem cells and suppresses tumorigenesis. The finding was also verified by using a mouse xenograft model of colon cancer. Masuda *et. al.* [167] found that small-molecule Traf2- and Nck-interacting kinase (TNIK) inhibitor, NCB-0846 could downregulate Wnt/β-catenin signaling by using *Tnik^{-/-}/Apc^{min/+}* mutant mice, which is essential to maintain the function of CSCs.

Translation of CSC research findings into anticancer drug development is still in the early stages [168]. The underlying mechanisms of how CSCs contribute to cancer progression are still not fully uncovered, and so efforts continue to unravel the biology [169-171]. However, CSCs remain a promising tool in anticancer drug development. Novel strategies such as nanomedicine targeting the CSC microenvironment are also being explored [172, 173].

Drug repositioning

Drug repositioning, an approach of finding new uses for existing drugs, has been attracting a lot of attention [22, 174]. By integrating different biological, chemical and genomics data profiles, drug repositioning can provide a rapid method to verify hypotheses and generate candidates for clinical validation. With the successful clinical application of non-cancer drugs for cancer treatment, drug repositioning becomes a powerful tool for anticancer development. Considering cancer often involves multiple pathologies [175], drug repositioning for combination therapy may be a promising direction [176].

Various drug repositioning approaches have been developed and could be potentially applied to anticancer drug development with initial evidence coming from preclinical models or controlled population studies (**Table 3**). The classic story is thalidomide, which was first marketed in 1957 in West Germany as a sedative and hypnotic. Afterward, it was also used

540 against nausea or alleviating morning sickness in pregnant women. However, severe adverse
541 reactions characterized by birth defects occurred and 60% of affected children died. Later,
542 researchers found thalidomide could inhibit NF- κ B and STAT3, and it was approved by the FDA
543 for treating multiple myeloma in 2006 Another example is metformin. Metformin, as a first-line
544 drug for type II diabetes, has been demonstrated to be an alternative therapy for multiple
545 cancers with both chemopreventive and chemotherapeutic functions by single or combination
546 therapy with other drugs [177-179]. The cancer prevention and anticancer activity of metformin
547 have been demonstrated in cell-based assays[180, 181], animal models [181, 182] and
548 controlled population studies [183]. Furthermore, aspirin as a nonsteroidal anti-inflammatory
549 drug (NSAID) has been reported to reduce cancer risk with regular intake. Currently, the world-
550 largest clinical Phase III trial is underway in the UK to evaluate aspirin for its potential
551 effectiveness to treat cancers such as breast, colorectal, and prostate [184].

552 The increasing interest in drug repositioning for anticancer treatment development is mainly
553 driven by the desire to use discontinued drugs and further exploit existing drugs with known
554 PK/PD properties and safety profiles [176]. Some promising directions for anticancer
555 repositioning include treating cancer by targeting the microenvironment, triggering immune
556 systems by approved drugs [185]. Brian *et. al.* [185] mapped 1309 drugs onto 221 immune cell
557 types based on their transcriptomic signature and predicted ~70,000 interactions. In addition,
558 the authors experimentally validated the influence of one candidate drug (clioquinol) on
559 neutrophil migration from the bone marrow to the blood in 6- to 12-week-old female C57Bl/c
560 mice to investigate how the drug perturbs the immune systems. The proposed methodology
561 may be useful for immune-related anticancer drug candidate profiling. However, attention
562 should be paid to the complex pathological and etiological features of cancers, which are very
563 different from other common diseases. For example, cancer patients are a vulnerable
564 population and a drug that does not have safety issues in healthier patients might trigger
565 problems for them, especially if used in novel combinations [186]. Furthermore, the rationale
566 behind non-cancer drugs treating cancer is that off-target effects driven by the
567 polypharmacology of non-cancer drugs could be beneficial to the cancer patients' survival. Since

the known PK/PD properties of non-cancer drugs are derived from data in the original indication, it is not guaranteed that the PK/PD features are still the same. Accordingly, the safety profiles should be also evaluated.

Concluding Remarks

By revisiting the anticancer drug development in the past two decades, we observe that a lot of encouraging progress has been made to improve cancer patients' survival and quality of life. Meanwhile, there are still a lot of hurdles and unsolved difficulties in anticancer drug development (see the **Outstanding Questions**). Furthermore, anticancer drugs tend to command extremely high prices due to unmet and urgent needs of the market and patients [187]. We have highlighted here some successes from the past twenty years, along with the challenges posed by translational from preclinical to clinical trials, from a small population to the larger population, and limited qualified biomarkers in the anticancer drug paradigm. All three of these issues draw attention to the need to reevaluate our current anticancer drug development tools and redefine clinical context for their implementation. With the advantage of biology, genetic engineering, and emerging techniques, more and more novel concepts such as precision oncology and animal models such as PDXs have been successfully applied to drive innovation in the anticancer drug discovery pipeline. However, utilization to truly harness these advances to facilitate and accelerate anticancer development is still suboptimal. Some uncertainties still exist with novel techniques, providing a barrier to robust and reliable results. It is suggested that more perspective-retrospective studies should be conducted to build the standards and guidance for application of novel anticancer development tools with multidisciplinary efforts from regulatory agencies, drugmakers, and academic researchers. We are delighted that a lot of activities have been advocated and promoted such as Cancer Moonshot [188], Patient-Reported Outcomes (PROs) [189, 190], FDA Biomarker Qualification Program, and PrecisionFDA, which build the communication bridges among the patients, drug-makers and regulatory agencies to move this field forward.

Anticancer drug development covers a wide spectrum of multidisciplinary fields. Some points not touched on and covered in depth here also hold promise in anticancer drug development. For example, genetic elements such as miRNAs also provide a new avenue for looking for cancer treatment options [191]. In addition, one of the gene therapies approach aims to add new genes to a patient's cells to replace missing or malfunctioning genes [192, 193], which may play an important role in future cancer treatment development with precise gene editing technologies such as CRISPR/Cas9 gene editing now available [194, 195]. Furthermore, cancer-derived induced pluripotent stem cells (iPSCs) also provide a tremendous opportunity to model the effects of the cancer genome back to animal models for anticancer drug discovery [50, 196, 197].

Anticancer drug development has shifted from conventional cytotoxics agents to targeted-based therapy and immunotherapy in the past two decades. Whether the new concepts and models truly fit within the established anticancer drug development paradigm is still an open question. A rethink of the existing anticancer drug discovery pipeline could refresh our minds to define pitfalls and further improve successful rates. Furthermore, cancer drug development is a collaborative activity that requires drug makers, researchers, patients and regulatory agencies to form a cohesive strategy to accelerate and improve drug development to improve the life quality of cancer patients.

Resources

The International Council for Harmonisation of Technical Requirements for Pharmaceuticals for Human Use (ICH) S9: <https://www.fda.gov/downloads/Drugs/Guidances/ucm085389.pdf>).

NCI cancer-related clinical trials: <https://www.cancer.gov/about-cancer/treatment/clinical-trials/advanced-search>

The International Council for Harmonisation of Technical Requirements for Pharmaceuticals for Human Use (ICH) M3: <https://www.fda.gov/downloads/Drugs/GuidanceComplianceRegulatoryInformation/Guidances/UCM292340.pdf>

621 Guidance for Industry Estimating the Maximum Safe Starting Dose in Initial Clinical Trials for
 622 Therapeutics in Adult Healthy Volunteers:
 623 <http://www.fda.gov/downloads/drugs/guidances/ucm078932.pdf>

624 Table of Pharmacogenomic Biomarkers in Drug Labeling:
 625 [https://www.fda.gov/Drugs/ScienceResearch/ResearchAreas/Pharmacogenetics/ucm083378.ht](https://www.fda.gov/Drugs/ScienceResearch/ResearchAreas/Pharmacogenetics/ucm083378.htm)
 626 [m](#)

627 FDA Biomarker Qualification Program:
 628 [https://www.fda.gov/Drugs/DevelopmentApprovalProcess/DrugDevelopmentToolsQualificatio](https://www.fda.gov/Drugs/DevelopmentApprovalProcess/DrugDevelopmentToolsQualificationProgram/BiomarkerQualificationProgram/default.htm)
 629 [nProgram/BiomarkerQualificationProgram/default.htm](#))

630 PrecisionFDA: <https://precision.fda.gov/>

631 Seed and soil hypothesis:
 632 <http://www.nature.com/milestones/milecancer/full/milecancer01.html>

633 NCI Cancer Statistics: <https://www.cancer.gov/about-cancer/understanding/statistics>

634 NCI drug repository: <https://www.cancer.gov/about-cancer/treatment/drugs>

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Table 1 Examples of Divergency in anticancer drug candidates between Phase II-III*

Drug names	Sponsor	Therapeutic target	Indication	Notes
Brivanib	Bristol-Myers Squibb	VEGFR and fibroblast growth factor receptors (FGFR)	hepatocellular cancer	Lack of efficiency. Brivanib failed to improve overall survival of patients compared to approved drug (i.e. sorafenib) and also demonstrated identified unexpected side effects.
Iniparib	Sanofi	Poly(adenosine diphosphate–ribose) polymerase 1 (PARP1)	Triple negative breast cancer	Lack of efficiency. It was demonstrated that Inspired with standard chemotherapy regimen (gemcitabine and carboplatin) could not improve survival
MAGE-A3 vaccine	GlaxoSmithKline	Antigen for immune responses	non-small cell lung cancer (NSCLC)	Lack of efficiency. The clinical benefit could be proved when compared to a placebo
Velimogene A lipasimid (Allovectin-7)	Vical	Antigen for cytotoxic T-cell and innate immune responses	metastatic melanoma	Lack of efficiency. Allovectin-7 reduced tumor size significantly fewer patients than another two market drugs (i.e. dacarbazine and temozolomide) for late-stage melanoma patients.
Figitumumab	Pfizer	insulin-like growth factor-1 receptor (IGF-1R)	non-small cell lung cancer (NSCLC)	Figitumumab with the standard regimen (paclitaxel and carboplatin) fails to improve the survival. Furthermore, severe adverse events (SAEs) such as pneumonia, dehydration and even death were observed

1039 * The data is from “22 Case Studies Where Phase 2 and Phase 3 Trials Had Divergent Results” and curated from
1040 <https://www.fda.gov/aboutfda/reportsmanualsforms/reports/ucm535541.htm>

Table 2 Failed and on-going examples of animal models in anticancer drug development

Animal model	Tumor type	Involved drug candidates	Notes	References
Failed examples				
Cynomolgus and rhesus monkeys	B-cell chronic lymphocytic leukemia (B-CLL)	TGN1412 (agonistic anti-CD28 antibody)	Severe inflammatory reactions to immune system in Phase I	[198, 199]
Mouse medulloblastoma model	Malignant solid brain tumor (medulloblastoma)/ Pancreatic Cancer	Saridegib (Hedgehog pathway antagonist)	Lack of efficiency when compared to placebo in clinical phase II	[200, 201]
Mouse-derived portion of the scFv on the CAR T cell	Acute lymphoblastic leukemia (ALL) as well as relapsed or refractory (r/r) chronic lymphocytic leukemia and non-Hodgkin lymphoma (NHL)	JCAR014 (a chimeric antigen receptor (CAR) T-cell receptor, targeting CD22)	Patients Death due to in Phase I dose-escalation trial	[202]

Table 3 Examples of drug repositioning for cancer therapy

Drug	Original indication	Suggested cancer mechanism	Models	Notes	References
pioglitazone	Type 2 diabetes	Multiple types		Pioglitazone could stabilize the elevated expression of the iron–sulfur (Fe-S) protein nutrient-deprivation autophagy factor-1 (NAF-1), which is a key factor to cancer cell progression.	[203]
Flavopiridol	Under clinical development of acute myeloid leukemia	Glioblastoma	Human glioblastoma cell lines	Flavopiridol is a synthetic flavonoid that inhibits a wide range of Cyclin-dependent kinase, that has demonstrated to inactivate glycogen phosphorylase, decreasing glucose availability for glycolysis. It is suggested flavopiridol could combine with anti-proliferative agents to treat glioblastoma.	[204]
rapamycin	lymphangioleiomyomatosis	pancreatic cancer	Genetically engineered	Targeted anti-mTOR therapies may offer clinical benefit in subsets of human	[205]

			mouse models	pancreatic ductal adenocarcinoma (PDAC) selected based on genotype	
diflunisal	Anti-inflammatory drug	leukemia	leukemia cell lines and mouse model	Diflunisal can suppress the growth of p300-dependent leukemia cell lines expressing AML1-ETO fusion protein in vitro and in vivo	[206]
chloroquine	antimalarial drug	Multiple cancers	normal cells in mice and cancer patients	chloroquine (CQ), is a robust inducer of Par-4 secretion from normal cells in mice and cancer patients in a clinical trial. CQ-inducible Par-4 secretion triggers paracrine apoptosis of cancer cells and inhibits metastatic tumor growth.	[207]
JQ1 in combination with romidepsin	romidepsin is used to cutaneous T-cell lymphoma (CTCL) and other peripheral T-cell lymphomas (PTCLs)	Type II testicular germ cell cancers (TGCT)	TGCT cell lines and Embryonal carcinoma (EC) xenografted mice models	JQ1 in combination with romidepsin could reduce tumor size, proliferation rate, and angiogenesis	[208]

metformin	Type 2 diabetes	Multiple types	Cancer cell line and mouse/rat models	Metformin can inhibit mTORC1 pathway, which plays a pivotal role in metabolism, growth, and proliferation of cancer cell.	[177, 178, 180, 181, 183]
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Figure Captions

- Figure 1** **Milestones in anticancer drug development in the past two decades**
- Figure 2** **The correlation between number of approved drugs and (A) percentage of survival in five years (2006~2012); (B) estimated newly added cases for each cancer type:** the statistics for each cancer type were based on the Surveillance, Epidemiology, and End Results (SEER) Program of the National Cancer Institute (<https://seer.cancer.gov/statfacts/>)
- Figure 3** **The key factors for translation of animal results to humans in anticancer drug development:** species selection, applicability of animal models, toxicity profiles, and PK/PD model optimization. FIH dose = first-in-human dose; MTD = maximum tolerated dose
- Figure 4** **New trends in anticancer drug development**

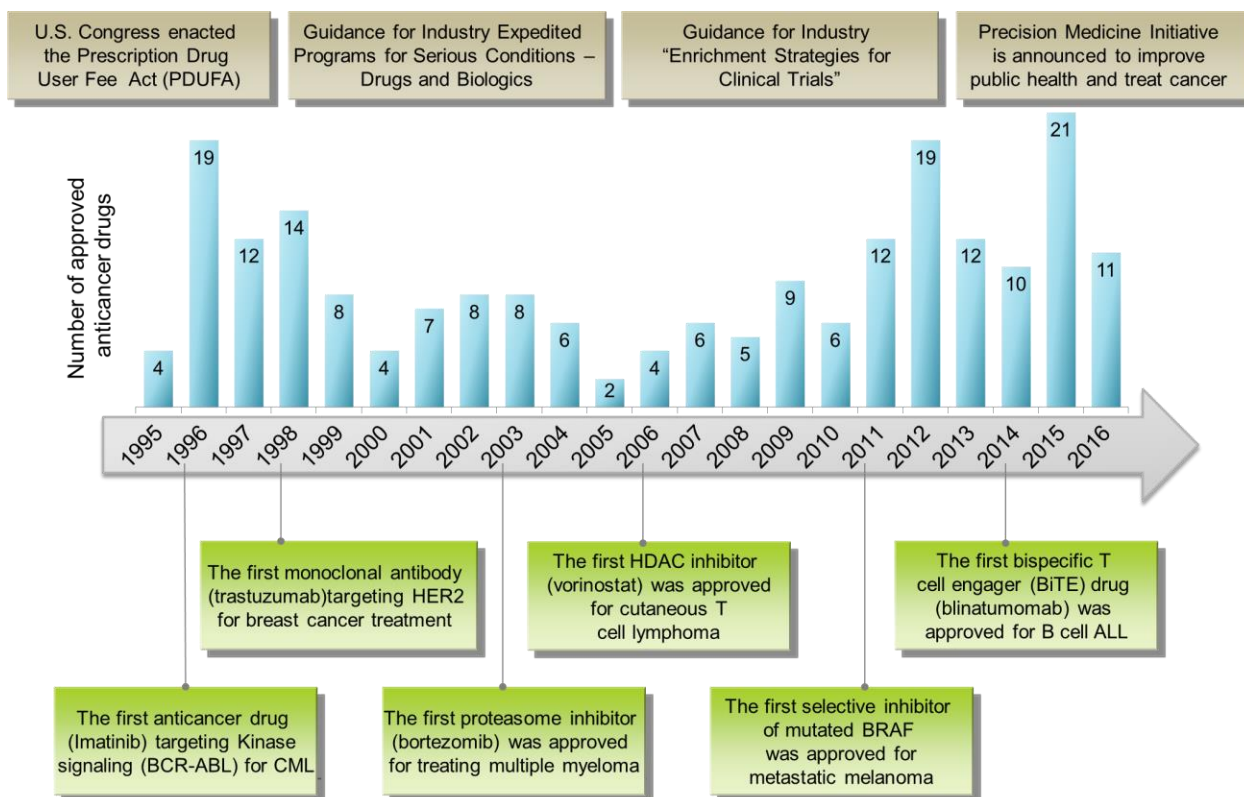


Figure 1

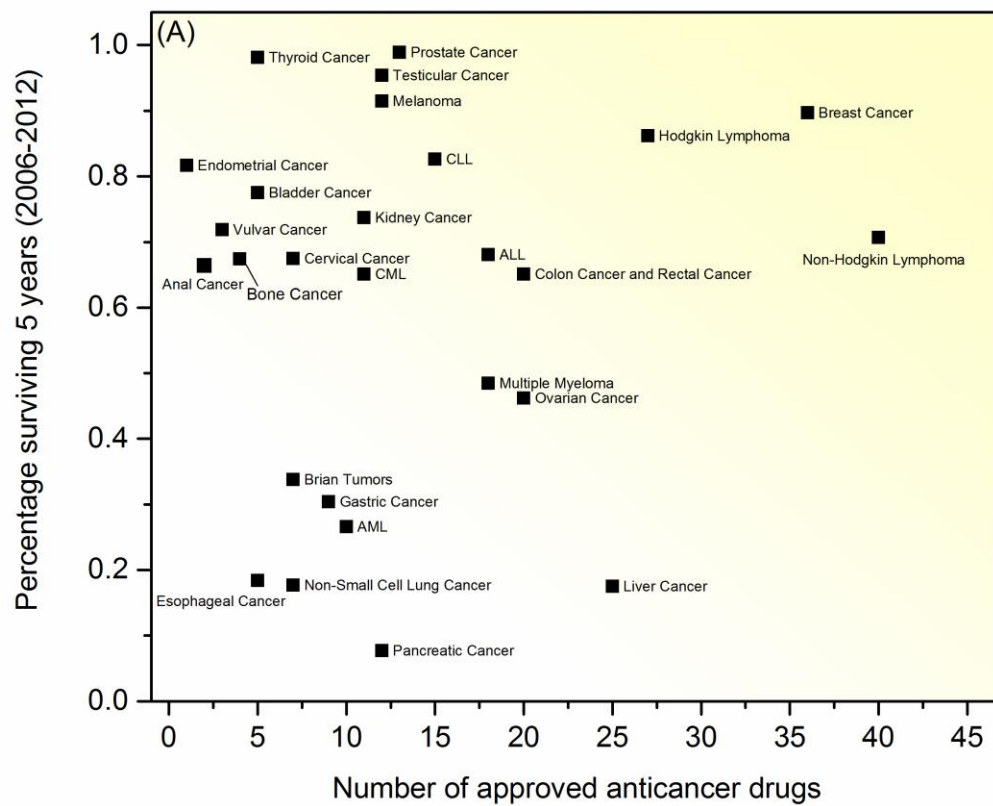


Figure 2(A)

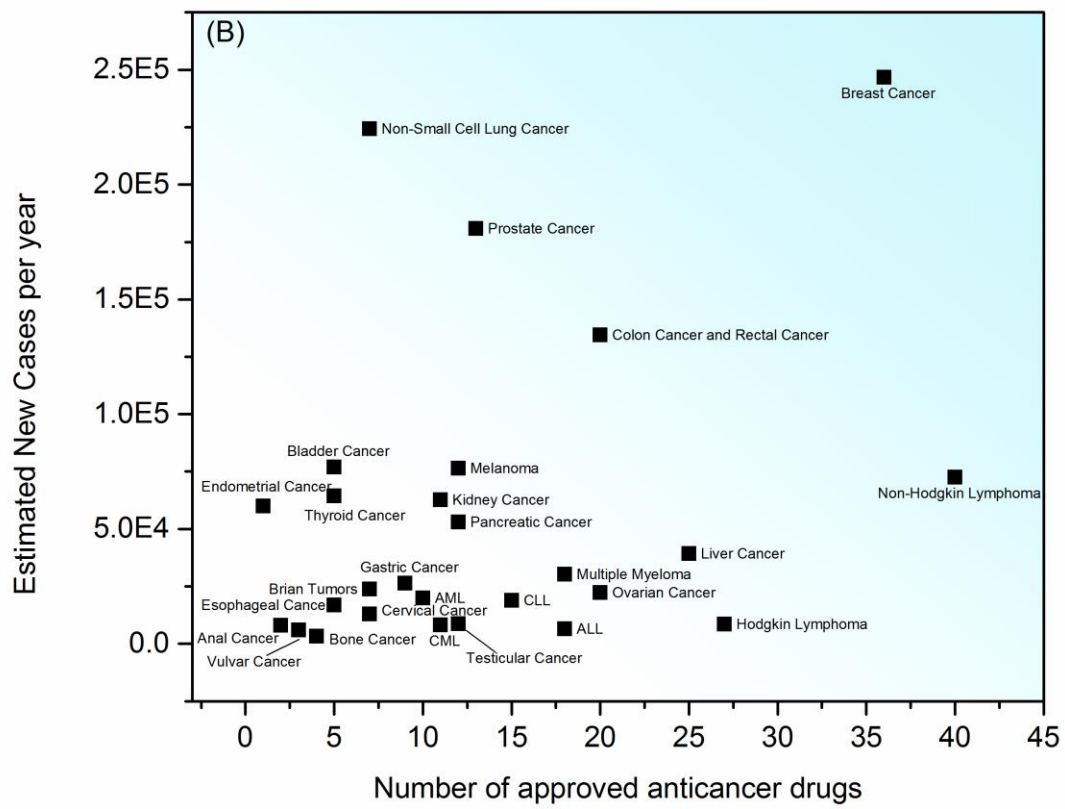


Figure 2(B)

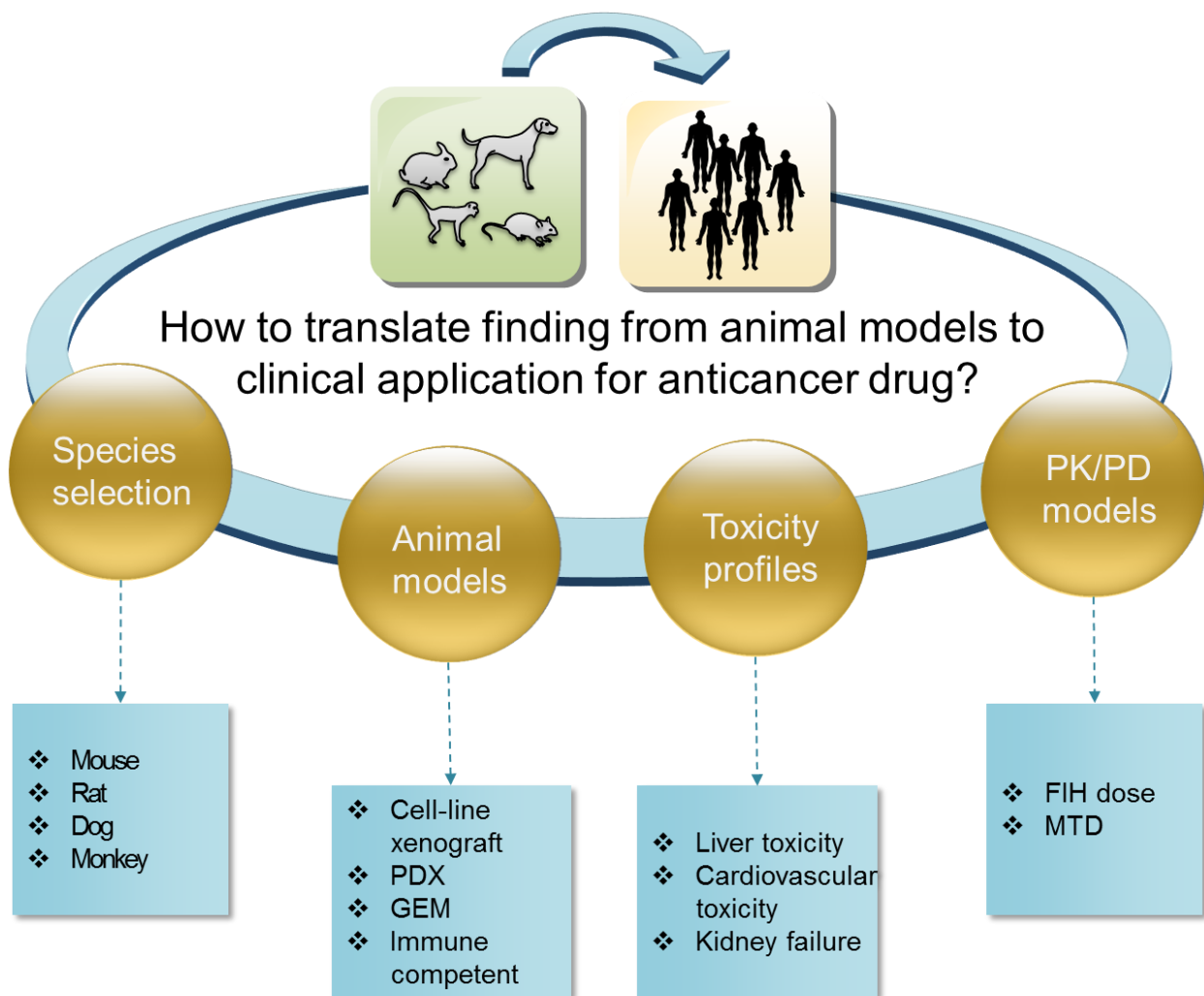


Figure 3

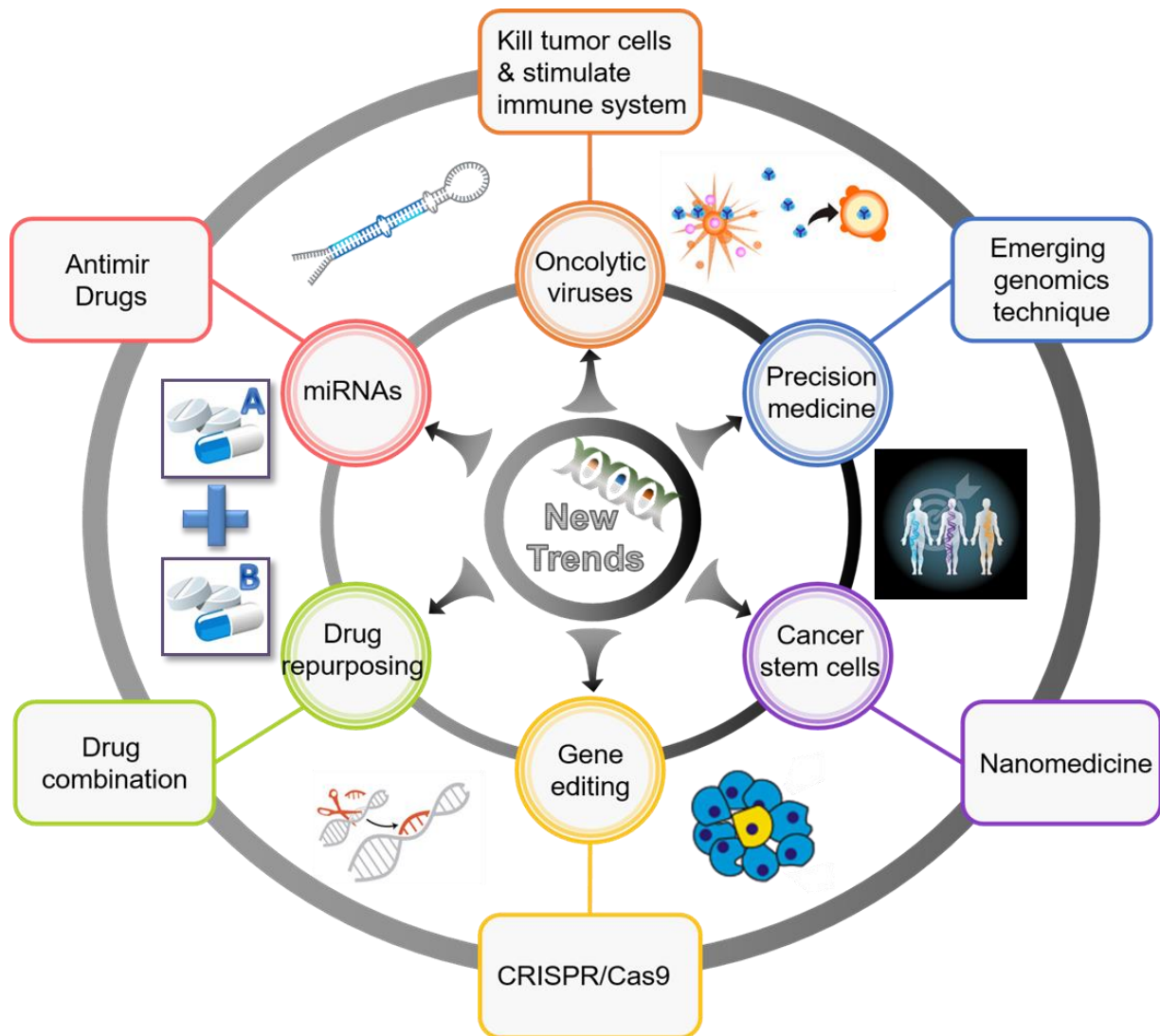


Figure 4