

ARTIFICIAL INTELLIGENCE-INTEGRATED SELF-EMULSIFYING DRUG DELIVERY SYSTEMS (AI-SEDDS)

DEVARAPALLI DEEPIKA¹, DUDDU VIJAY KUMAR², KUNISETTY LIKHITHA³, MATANGI SAGAR⁴, RAVI SRAVANA SINDHU⁵, Y. GOVINDA RAO⁶

Malineni Perumallu Pharmacy College, Pulladigunta, Guntur-522017, A.P, India.

*CORRESPONDING AUTHOR

Dr. Y. Govinda Rao

DOI: <https://doi.org/10.37022/baddt.v1i2.965>

Article History: Received: 14.07.2026, Revised: 03.08.2026, Accepted: 22.09.2026

ABSTRACT

Self-emulsifying drug delivery systems (SEDDS) are lipid-based formulations generally containing oil, surfactant and co-surfactant or a cosolvent. Dilution results in formation of fine dispersions, enabling solubilization of lipophilic drugs and/or improving their dissolution and/or absorption. While formulation of SEDDS remains largely empirical and requires extensive experimentation, artificial intelligence (AI) can be leveraged for predictive excipient selection, design of critical quality attribute (CQA) space, multi-objective optimization, precipitation risk ranking and active design of experiments. This review proposes an AI-integrated SEDDS loop encompassing molecular descriptors, excipients, formulation design, gastrointestinal performance and pharmacokinetic (PK) outcomes. Bayesian optimization, explainable AI, supersaturable and solid SEDDS, digital twin and self-driving lab concepts are also discussed. The overall perspective is that AI should complement traditional pharmaceutical experimentation and that standardized dataset creation and external validation are critical enablers.

Keywords: Self-emulsifying drug delivery systems; SEDDS; SMEDDS; SNEDDS; Artificial intelligence; Machine learning; Lipid-based drug delivery; Oral bioavailability; Bayesian optimization; Quality by Design; Digital twin.

This article is licensed under a Creative Commons Attribution-Non-commercial 4.0 International License. Copyright © 2026 Author(s) retains the copyright of this article.

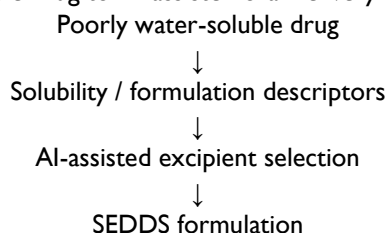


1. INTRODUCTION

Poor aqueous solubility is a common limitation for oral delivery of hydrophobic drugs and molecules with limited capacity to dissolve upon gastrointestinal fluids contact. Lipid-based formulations offer a viable approach to enhance drug solubilization and enable absorption through the intestinal lining. Self-emulsifying drug delivery systems (SEDDS) are particularly useful due to their ability to form emulsions or disperse upon dilution with aqueous media after oral administration. The classification system for lipid-based formulations has provided valuable insights into relationships between formulation composition, digestion and absorption [1-2].

Conventional SEDDS development typically involves drug solubility screening in selected excipients, design of pseudo-ternary phase diagrams; Design of Experiments (DoE) based optimization of oil/surfactant/co-surfactant ratios and finally, evaluation of the resulting formulations in terms of physicochemical properties, dissolution and in vivo performance. While these approaches have been generally successful, the complexity of formulation variables and their non-linear interactions make formulation development challenging. With increased availability of formulation datasets, machine learning (ML) can be leveraged for predictive formulation design. Previously, ML has been successfully applied for drug solubility predictions in lipid vehicles. At the same time, drug-delivery reviews highlight AI-assisted formulation design, formulation space exploration and self-driving platforms [3-4].

The given flow chart is about poorly soluble drug to AI-assisted oral delivery



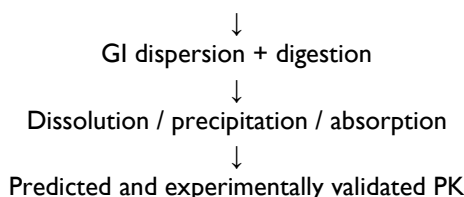


Figure 01: Practical Classification of Self Emulsifying Systems

2. SEDDS: FUNDAMENTAL CONCEPT

SEDDS are isotropic mixtures of lipids and surfactants, with optional co-surfactants or cosolvents that upon dilution in water and gentle agitation result in formation of emulsified or dispersed systems [5]. The formation of fine emulsions enhances absorption by increasing the surface area available for interaction with the gastrointestinal (GI) fluids. Lipid digestion and interaction with bile components can further contribute to solubilization, redistribution and absorption [6-7].

Table 01: Comparison of Different Self-Emulsifying Drug Delivery Systems Based on Particle Size, Appearance, and Key Characteristics

System	Practical size range	Typical appearance	Main characteristic
SEDDS	~250 nm to several μm	Cloudy/turbid	Conventional self-emulsification
SMEDDS	~100–250 nm	Clear/translucent	Fine microemulsion-like dispersion
SNEDDS	Often <100 nm	Clear/near-clear	Nano-sized dispersion
Su-SEDDS	Variable	Clear/translucent	Designed to maintain supersaturation
Solid SEDDS	Reconstituted size varies	Powder/tablet before reconstitution	Liquid system converted to solid dosage form

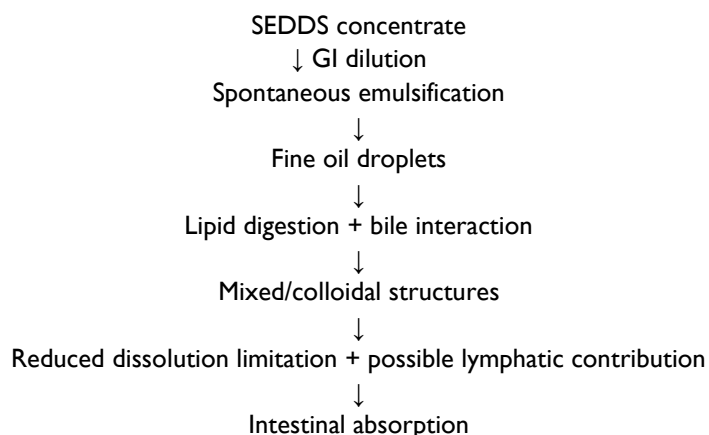


Figure 02: Proposed mechanism of SEDDS-mediated oral absorption

3. COMPONENTS OF SEDDS

The oil component generally plays a major role in solubilization of the drug and is digested and potentially transported via the lymphatic pathway. Surfactants reduce interfacial tension and aid emulsification while co-surfactants and cosolvents improve flexibility at the interface and solubilization capacity [8]. Consideration must be given to each component's impact on drug solubilization, self-emulsification, tolerability and stability [9].

Table 02: Major SEDDS components and their potential AI descriptors

Component	Examples	Primary role	AI-relevant descriptors
Oil	MCTs, long-chain triglycerides, mono-/diglycerides, fatty acids	Drug solubilization; digestion substrate	Fatty-acid profile, polarity, viscosity, HLB-related descriptors
Surfactant	Polysorbates,	Interfacial stabilization	HLB, CMC, molecular

	Cremophor/Kolliphor, Labrasol		descriptors
Co-surfactant	PEG 400, Transcutol, propylene glycol	Interfacial flexibility	Polarity, molecular weight
Co-solvent	Ethanol, PEGs	Drug solubilization	Dielectric/polarity descriptors
Precipitation inhibitor	Polymers such as HPMC derivatives	Maintain supersaturation	Molecular weight, functional groups
Solid carrier	Porous silica, adsorbents, solid excipients	Solidification	Surface area, porosity, adsorption capacity

4. CONVENTIONAL FORMULATION DEVELOPMENT

Typically, drug solubility is screened in representative excipients. Based on solubility, combinations of surfactant/oil are selected and pseudo-ternary phase diagrams are constructed [10]. This is followed by optimization and characterization according to standard procedures [Figure 3]. While generally robust, such development campaigns can become tedious due to the number of excipients considered and composition ranges evaluated [12-15].

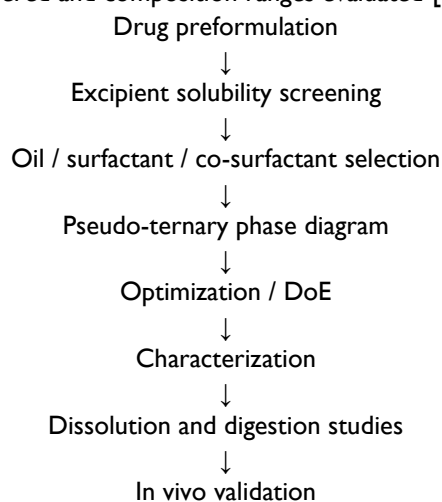


Figure 03: Conventional SEDDS development workflow

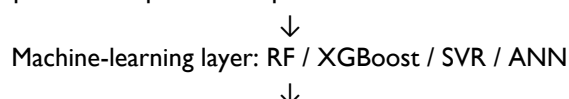
Table 03: Limitations of conventional SEDDS development.

Problem	Conventional approach	Main limitation
Excipient screening	Individual solubility experiments	Large experimental matrix
Composition optimization	DoE / trial-and-error	May require many runs
Droplet-size control	Iterative formulation	Nonlinear composition effects
Precipitation	Post-formulation testing	Late discovery of risk
Bioavailability	In vivo studies	Expensive and low throughput

5. WHY AI FITS SEDDS DEVELOPMENT

SEDDS formulation is a multi-variable and multi-objective optimization problem. ML can play a critical role in such contexts by building predictive models of formulation behaviour [16-17]. A typical formulation needs to maximize drug loading and dissolution while also minimizing droplet size, PDI, precipitation and surfactant exposure, among others. Moreover, a formulation's performance has to be tested in terms of a variety of CQAs. Thus, ML, surrogate modeling and Bayesian optimization can be valuable additions to conventional design of experiments-based approaches [18-20].

Drug molecular descriptors + Excipient descriptors + Formulation variables + Process variables



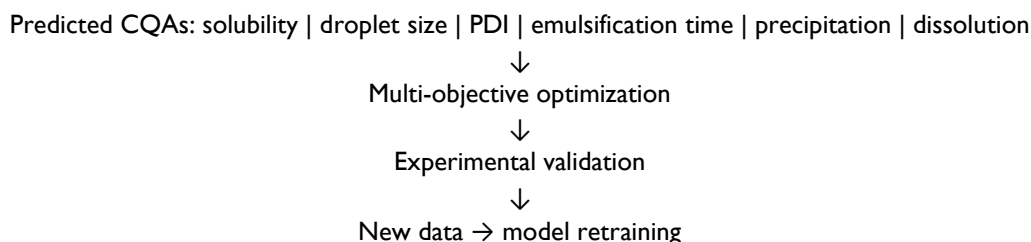


Figure 04: Proposed AI-SEDDS architecture

6. AI-BASED EXCIPIENT SELECTION

AI-assisted excipient selection involves ranking of candidate excipients based on molecular descriptors and fingerprints [21-22]. The initial screening would focus on those excipients that can enhance drug solubilization. In this regard, an ML approach, Sol_ME, was created recently for prediction of drug solubility in lipidic media using molecular fingerprints [23-26].

Table 04: Proposed AI feature space for excipient selection

Input category	Examples	Potential prediction
Drug descriptors	MW, logP, TPSA, H-bonding, melting point	Lipid/excipient solubility
Oil descriptors	Fatty-acid profile, polarity, viscosity	Drug solubilization
Surfactant descriptors	HLB, CMC, molecular structure	Emulsification performance
Co-surfactant descriptors	Polarity, molecular weight	Interfacial behaviour
Drug–excipient fingerprints	Structural similarity / interaction features	Compatibility ranking

7. AI PREDICTION OF CRITICAL QUALITY ATTRIBUTES

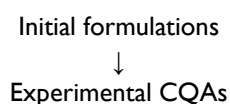
Critical quality attributes for SEDDS include droplet size and polydispersity index (PDI), zeta potential, self-emulsification time, drug content, drug loading, robustness to dilution, dissolution and physical stability. ML can be utilized to predict these CQAs as functions of formulation variables and process parameters. However, it is critical that such models undergo external validation [27-29].

Table 05: AI mapping of SEDDS formulation variables to CQAs.

Input variables	Candidate model	Predicted CQA
Oil/surfactant/co-surfactant ratio	Random Forest / XGBoost	Droplet size
Composition + process conditions	ANN / SVR	PDI
Drug + excipient descriptors	RF / XGBoost	Drug loading
Composition + digestion data	Hybrid ML	Precipitation risk
Formulation + dissolution profile	ANN / gradient boosting	Dissolution performance

8. BAYESIAN OPTIMIZATION AND ACTIVE LEARNING

Bayesian optimization is particularly useful in the context of experiments with prohibitively high costs. Instead of exploring all formulations, an initial subset can be utilized to build a surrogate model that approximates the relationship between input variables and response(s). The next set of experiments can then focus on maximizing the acquisition function, i.e., balancing the predicted response and uncertainty around it. This leads to active learning, a form of iterative ML training [30-33].



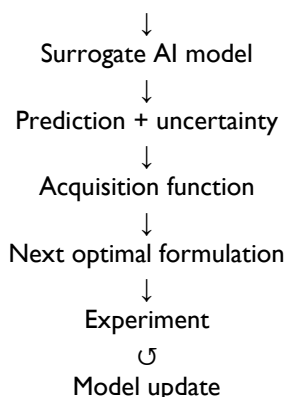


Figure 05: Bayesian optimization loop for SEDDS.

9. SUPERSATURABLE SEDDS AND AI

A key challenge with lipid-based systems is drug precipitation upon dilution following digestion. Typically, the formulation contains a drug amount higher than its solubility in the resulting aqueous media. Consequently, a supersaturated solution forms upon dilution, which precipitates out upon nucleation and crystal growth. Such a propensity can be mitigated by utilizing precipitation inhibitors to maintain supersaturation for extended times [34,36]. Here, AI can be used both for predicting precipitation risk and determining the optimal level of inhibitor to minimize such risks [37-38].

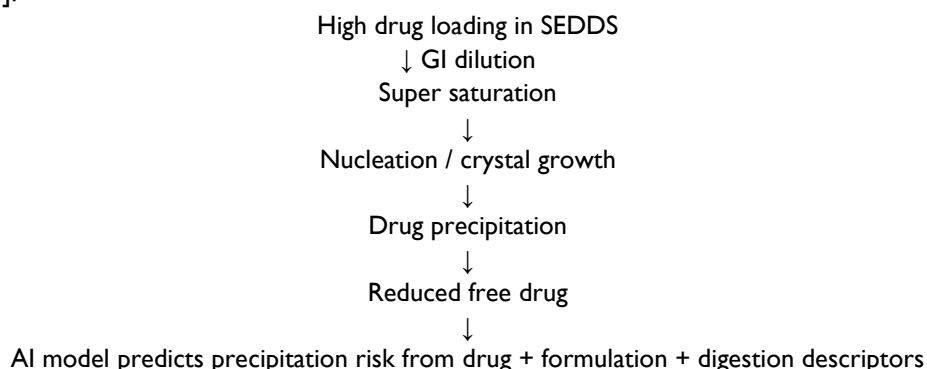


Figure 06: Proposed AI model for precipitation-risk prediction

10. SOLID SEDDS AND AI

Liquids can be challenging to handle, dose and stabilize. Solidification can be achieved by various means such as absorption onto solid carriers, spray-drying, melt-related approaches and others. Similarly to conventional SEDDS, solid SEDDS can benefit from AI-assisted design [39].

Table 06: AI opportunities in solid SEDDS development

Solidification strategy	Key variables	Potential AI output
Adsorption	Carrier surface area, lipid: carrier ratio	Adsorption capacity / flowability
Spray drying	Inlet temperature, feed rate, solids content	Yield, moisture, redispersibility
Granulation	Binder level, process conditions	Granule properties
Compression	Compression force, excipient ratio	Tablet CQAs
Reconstitution	Dilution medium, formulation composition	Droplet size / PDI

11. AI + GASTROINTESTINAL DIGESTION

While droplet size is clearly a key determinant of SEDDS performance, it should be noted that SEDDS formulations undergo dilution and lipolysis followed by interaction with bile components and drug redistribution prior to intestinal absorption. Incorporating in vitro digestion data into the framework can enable AI to make more accurate predictions of drug solubilization and absorption [40].

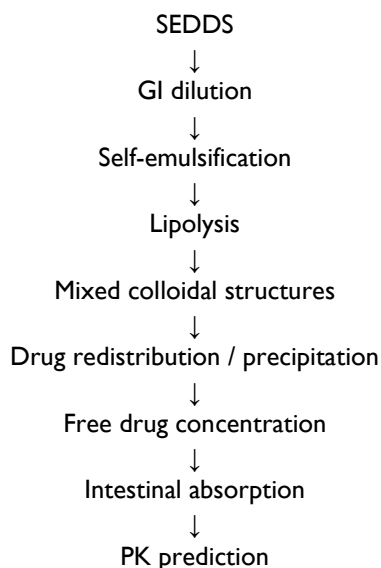


Figure 07: Proposed GI digestion-to-PK AI framework

Table 07: Proposed AI integration with gastrointestinal SEDDS behaviour.

GI parameter	Experimental measurement	Potential AI input	Prediction
Dilution	Media volume / ratio	Dilution descriptors	Dispersion behaviour
Lipolysis	In vitro lipolysis	Digestion kinetics	Drug solubilization
Precipitation	Turbidity / concentration / solid analysis	Supersaturation descriptors	Precipitation risk
Absorption	Permeation / PK	Exposure descriptors	AUC / Cmax trend

12. DIGITAL TWIN CONCEPT FOR SEDDS

A digital twin is postulated here as a comprehensive digital representation of a physical SEDDS formulation. It can incorporate formulation composition, mechanistic digestion models, ML predictions and PK information to create a virtual twin of the formulation. Such a tool may ultimately be valuable in accelerating formulation development [41].

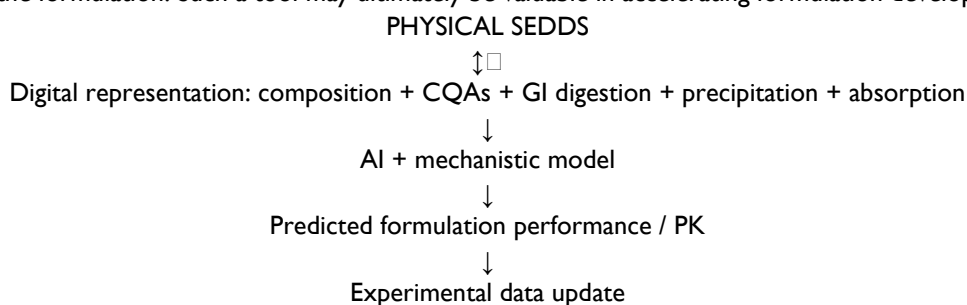
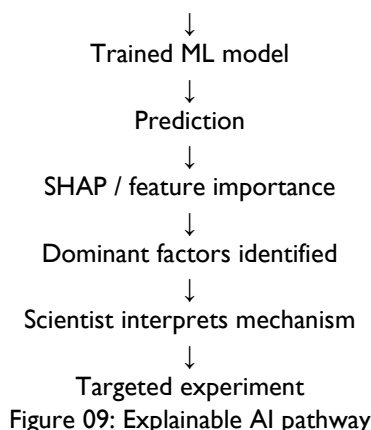


Figure 08: Proposed SEDDS digital twin

13. EXPLAINABLE AI IN SEDDS

While prediction accuracy is critical, it is also essential that AI models be interpretable. The utilization of explainable AI models such as SHAP values can help identify the input variables that drive predictions and assist in determining mechanistic relationships [42].

Formulation data



14. MULTI-OBJECTIVE OPTIMIZATION

Formulation of SEDDS typically involves simultaneous consideration of multiple criteria. Multi-objective optimization allows the identification of a set of formulations that are optimal according to multiple criteria [43].

Table 08: Multi-objective optimization targets for AI-SEDDS

Objective	Desired direction	Reason
Drug loading	Increase	Reduce formulation volume
Dissolution	Increase	Improve availability
Bioavailability	Increase	Improve systemic exposure
Droplet size	Decrease	Increase interfacial area
PDI	Decrease	Improve dispersion uniformity
Precipitation	Decrease	Maintain solubilized drug
Surfactant exposure	Decrease	Support tolerability
Manufacturing complexity	Decrease	Improve scalability

15. CHARACTERIZATION OF AI-OPTIMIZED SEDDS

Table 09: Characterization strategy for AI-optimized seeds

Test	Typical technique	Purpose	AI relevance
Droplet size	DLS	Size distribution	Model target
PDI	DLS	Uniformity	Model target
Zeta potential	Electrophoretic measurement	Surface characteristics	Stability feature
Self-emulsification	Visual/turbidity or timed test	Dispersion performance	Model target
Drug content	HPLC/UV	Assay	Quality control
Dissolution	USP dissolution apparatus	Drug release	Model target
Solid state	DSC / PXRD	Physical state	Precipitation/solidification evidence
Morphology	SEM/TEM where appropriate	Structural assessment	Mechanistic validation
In vitro lipolysis	Biorelevant digestion model	Drug solubilization during digestion	AI training feature

16. QUALITY BY DESIGN + AI

AI can be utilized within a quality-by-design (QbD) paradigm rather than as a stand-alone tool. A typical QbD-based formulation campaign would involve identification of target product profile (QTPP), critical quality attributes (CQAs) and critical material attributes (CMAs) and process parameters (CPPs); AI-based risk ranking; design space identification and experimental verification; and finally, control strategy design [44].

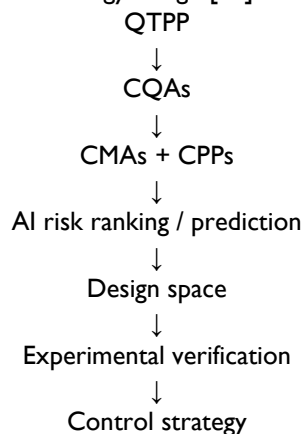


Figure 10: AI-enhanced QbD framework

17. SELF-DRIVING SEDDS LABORATORY

Perhaps in the more distant future, a self-driving formulation lab could be envisioned in which AI picks the next formulation, robots prepare it, analytical instruments characterize it, and the data are sent back to the model for training. Such a closed-loop formulation lab is a valuable long-term goal that requires substantial investment and data integrity [45-47].

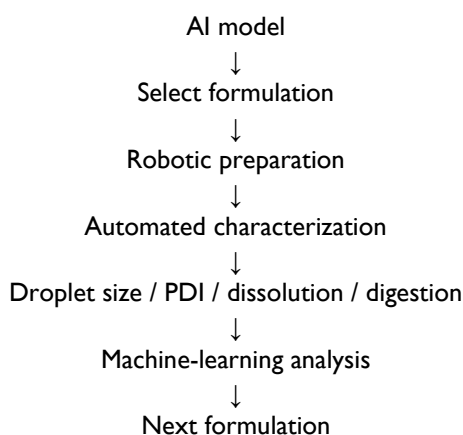


Figure 11: Proposed self-driving SEDDS laboratory

18. ADVANTAGES AND LIMITATIONS

Table 10: Advantages and limitations of AI-integrated SEDDS

Area	Potential advantage	Key limitation
Excipient screening	Rank candidates before experiments	Requires reliable training data
Optimization	Reduce unnecessary experiments	Model may extrapolate poorly
CQA prediction	Early risk identification	Needs external validation
Precipitation	Early warning	GI conditions are complex
Automation	High-throughput learning	High infrastructure cost
Interpretability	Feature importance can guide science	Explainability does not prove mechanism

19. RESEARCH GAPS AND FUTURE DIRECTIONS

Table 11: Major research gaps and proposed solutions

Research gap	Why important	Proposed direction
Small datasets	Limits generalization	Federated/pooled standardized datasets
Data heterogeneity	Different test conditions	Common reporting ontology
Missing negative data	Bias toward successful formulations	Archive failed experiments
Black-box models	Weak scientific interpretability	Explainable and hybrid models
Limited GI modelling	Droplet size does not equal bioavailability	Mechanistic + ML models
Scale-up uncertainty	Lab and manufacturing differ	Digital twins and process data
Regulatory uncertainty	AI outputs require traceability	Validated, version-controlled models

20. CONCLUSION

AI-integrated SEDDS represent a major opportunity to transition from empirical to predictive pharmaceutical development. The most valuable applications are likely to come from combining AI with traditional formulation science rather than relying on either exclusively. An AI-driven SEDDS loop encompasses molecular descriptors, excipient selection, formulation, gastrointestinal behaviour and experimental outcomes. ML can be leveraged for excipient ranking and CQA prediction, Bayesian optimization can reduce redundant experimentation, explainable AI can guide scientific discovery and hybrid mechanistic-AI models can provide deeper insights into GI digestion and absorption. Solid SEDDS, supersaturable systems, digital twins and self-driving lab concepts also offer exciting opportunities for advancing lipid-based drug delivery. The most pressing requirement is the establishment of standardized, validated data sets with sufficient information for training and applying AI models in formulation development.

21. FUNDING

Nil

22. CONFLICT OF INTEREST

Not applicable

23. INFORM CONSENT AND ETHICAL DECLARATIONS

Not Applicable

24. ACKNOWLEDGEMENT

Not applicable

25. REFERENCES

1. Pouton CW. Lipid formulations for oral administration of drugs: non-emulsifying, self-emulsifying and 'self-microemulsifying' drug delivery systems. Eur J Pharm Sci. 2000;11 Suppl 2:S93-S98. doi:10.1016/S0928-0987(00)00167-6.
2. Pouton CW. Formulation of poorly water-soluble drugs for oral administration: physicochemical and physiological issues and the lipid formulation classification system. Eur J Pharm Sci. 2006;29(3-4):278-287. doi:10.1016/j.ejps.2006.04.016.
3. Pouton CW, Porter CJH. Formulation of lipid-based delivery systems for oral administration: materials, methods and strategies. Adv Drug Deliv Rev. 2008;60(6):625-637. doi:10.1016/j.addr.2007.10.010.
4. Porter CJH, Trevaskis NL, Charman WN. Lipids and lipid-based formulations: optimizing the oral delivery of lipophilic drugs. Nat Rev Drug Discov. 2007;6(3):231-248. doi:10.1038/nrd2197.

5. Hauss DJ. Oral lipid-based formulations. *Adv Drug Deliv Rev.* 2007;59(7):667-676. doi:10.1016/j.addr.2007.05.006.
6. Kohli K, Chopra S, Dhar D, Arora S, Khar RK. Self-emulsifying drug delivery systems: an approach to enhance oral bioavailability. *Drug Discov Today.* 2010;15(21-22):958-965. doi:10.1016/j.drudis.2010.08.007.
7. Singh B, Bandopadhyay S, Kapil R, Singh R, Katare OP. Self-emulsifying drug delivery systems (SEDDS): formulation development, characterization, and applications. *Crit Rev Ther Drug Carrier Syst.* 2009;26(5):427-521. doi:10.1615/critrevtherdrugcarriersyst.v26.i5.10.
8. Gursoy RN, Benita S. Self-emulsifying drug delivery systems (SEDDS) for improved oral delivery of lipophilic drugs. *Biomed Pharmacother.* 2004;58(3):173-182. doi:10.1016/j.biopha.2004.02.001.
9. Shah NH, Carvajal MT, Patel CI, Infeld MH, Malick AW. Self-emulsifying drug delivery systems with polyglycolized glycerides. *Int J Pharm.* 1994;106(1):15-23. doi:10.1016/0378-5173(94)90271-2.
10. Humberstone AJ, Charman WN. Lipid-based vehicles for the oral delivery of poorly water soluble drugs. *Adv Drug Deliv Rev.* 1997;25(1):103-128. doi:10.1016/S0169-409X(96)00494-2.
11. Porter CJH, Charman WN. In vitro assessment of oral lipid based formulations. *Adv Drug Deliv Rev.* 2001;50 Suppl 1:S127-S147. doi:10.1016/S0169-409X(01)00182-X.
12. Your original reference appears to be incorrect. The verifiable paper is: Mu H, Holm R, Müllertz A. Lipid-based formulations for oral administration of poorly water-soluble drugs. *Int J Pharm.* 2013;453(1):215-224. doi:10.1016/j.ijpharm.2013.03.054.
13. Feeney OM, Crum MF, McEvoy CL, Trevaskis NL, Williams HD, Pouton CW, et al. 50 years of oral lipid-based formulations: provenance, progress and future perspectives. *Adv Drug Deliv Rev.* 2016;101:167-194. doi:10.1016/j.addr.2016.04.007.
14. Gershanik T, Benita S. Self-dispersing lipid formulations for improving oral absorption of lipophilic drugs. *Eur J Pharm Biopharm.* 2000;50(1):179-188. doi:10.1016/S0939-6411(00)00089-8.
15. O'Driscoll CM, Griffin BT. Biopharmaceutical challenges associated with drugs with low aqueous solubility--the potential impact of lipid-based formulations. *Adv Drug Deliv Rev.* 2008;60(6):617-624. doi:10.1016/j.addr.2007.10.012.
16. Thomas N, Holm R, Rades T, Müllertz A. Characterising lipid lipolysis and its implication in lipid-based formulation development. *AAPS J.* 2012;14(4):860-871. doi:10.1208/s12248-012-9398-6.
17. Müllertz A, Ogbonna A, Ren S, Rades T. New perspectives on lipid and surfactant based drug delivery systems for oral delivery of poorly soluble drugs. *J Pharm Pharmacol.* 2010;62(11):1622-1636. doi:10.1111/j.2042-7158.2010.01107.x.
18. Williams HD, Trevaskis NL, Charman SA, Shanker RM, Charman WN, Pouton CW, et al. Strategies to address low drug solubility in discovery and development. *Pharmacol Rev.* 2013;65(1):315-499. doi:10.1124/pr.112.005660.
19. MacGregor KJ, Embleton JK, Lacy JE, Perry EA, Solomon LJ, Seager H, et al. Influence of lipolysis on drug absorption from the gastrointestinal tract. *Adv Drug Deliv Rev.* 1997;25(1):33-46. doi:10.1016/S0169-409X(96)00489-9.
20. Fatouros DG, Müllertz A. In vitro lipid digestion models in design of drug delivery systems for enhancing oral bioavailability. *Expert Opin Drug Metab Toxicol.* 2008;4(1):65-76. doi:10.1517/17425255.4.1.65. Your original journal title and page range were incorrect.
21. Cuiné JF, McEvoy CL, Charman WN, Pouton CW. Evaluation of medium-chain triglyceride formulations to enhance oral bioavailability. *Int J Pharm.* 2007;329(1-2):73-80. doi:10.1016/j.ijpharm.2006.08.020.
22. Porter CJH, Kaukonen AM, Boyd BJ, Edwards GA, Charman WN. Susceptibility to lipase-mediated digestion reduces the oral bioavailability of danazol after administration as a medium-chain lipid-based microemulsion formulation. *Pharm Res.* 2004;21(8):1405-1412. doi:10.1023/B:PHAM.0000036914.22132.cc.
23. Porter CJH, Pouton CW, Cuiné JF, Charman WN. Enhancing intestinal drug solubilisation using lipid-based delivery systems. *Adv Drug Deliv Rev.* 2008;60(6):673-691. doi:10.1016/j.addr.2007.10.014.
24. Williams HD, Sassene P, Kleberg K, Bakala-N'Goma JC, Calderone M, Jannin V, et al. Toward the establishment of standardized in vitro tests for lipid-based formulations, part I: method parameterization and comparison of in vitro digestion profiles across a range of representative formulations. *J Pharm Sci.* 2012;101(9):3360-3380. doi:10.1002/jps.23205. Your original journal, volume and pages were incorrect.
25. Porter CJH, Trevaskis NL, Charman WN. Lipids and lipid-based formulations: optimizing the oral delivery of lipophilic drugs. *Nat Rev Drug Discov.* 2007;6(3):231-248. doi:10.1038/nrd2197.
26. Singh B, Bandopadhyay S, Kapil R, Singh R, Katare OP. Self-emulsifying drug delivery systems (SEDDS): formulation development, characterization, and applications. *Crit Rev Ther Drug Carrier Syst.* 2009;26(5):427-521. doi:10.1615/critrevtherdrugcarriersyst.v26.i5.10.
27. Singh S, Bajpai M, Mishra P. Self-emulsifying drug delivery system: an emerging dosage form to improve bioavailability of poorly absorbed drugs. *Crit Rev Ther Drug Carrier Syst.* 2020;37(4):305-329.
28. Bernkop-Schnürch A, Müllertz A, Rades T. Self-emulsifying drug delivery systems (SEDDS): the splendid comeback of an old technology. *Adv Drug Deliv Rev.* 2019;142:1-2. doi:10.1016/j.addr.2019.08.002.
29. Mahmood A, Bernkop-Schnürch A. SEDDS: a game changing approach for the oral administration of hydrophilic macromolecular drugs. *Adv Drug Deliv Rev.* 2019;142:91-101. doi:10.1016/j.addr.2018.07.001.

30. Buya AB, Beloqui A, Memvanga PB, Pr  at V. Self-nano-emulsifying drug-delivery systems: from the development to the current applications and challenges in oral drug delivery. *Pharmaceutics*. 2020;12(12):1194. doi:10.3390/pharmaceutics12121194.
31. Almeida SRD, Tippavajhala VK. A rundown through various methods used in the formulation of solid self-emulsifying drug delivery systems (S-SEDDS). *AAPS PharmSciTech*. 2019;20(8):323. doi:10.1208/s12249-019-1550-5.
32. Pehlivanov I. Self-emulsifying drug delivery systems (SEDDS): excipient selection, formulation and characterization. *J IMAB*. 2020;26(3):3226-3233. doi:10.5272/jimab.2020263.3226.
33. Kadian R, Nanda A. A comprehensive insight on self emulsifying drug delivery systems. *Recent Adv Drug Deliv Formul*. 2022;16(1):16-44. doi:10.2174/2667387815666211207112803.
34. Park H, Ha ES, Kim MS. Current status of supersaturable self-emulsifying drug delivery systems. *Pharmaceutics*. 2020;12(4):365. doi:10.3390/pharmaceutics12040365.
35. Salawi A. Self-emulsifying drug delivery systems: a novel approach to deliver drugs. *Drug Deliv*. 2022;29(1):1811-1823. doi:10.1080/10717544.2022.2083724. Your original journal was incorrect.
36. Gupta S, Kesarla R, Omri A. Formulation strategies to improve the bioavailability of poorly absorbed drugs with special emphasis on self-emulsifying systems. *ISRN Pharm*. 2013;2013:848043. doi:10.1155/2013/848043.
37. Rahman MA, Harwansh R, Mirza MA, Hussain S, Hussain A. Oral lipid based drug delivery system (LBDDS): formulation, characterization and application: a review. *Curr Drug Deliv*. 2011;8(4):330-345. doi:10.2174/156720111795767906.
38. Wang G, Wang J, Wu W, To SST, Zhao H, Wang J. Advances in lipid-based drug delivery: enhancing efficiency for hydrophobic drugs. *Expert Opin Drug Deliv*. 2015;12(9):1295-1309. doi:10.1517/17425247.2015.1021681.
39. Larsen AT,   kesson P, Jur  us A, Saaby L, Abu-Rmaileh R, Abrahamsson B, et al. Bioavailability of cinnarizine in dogs: effect of SNEDDS loading level and correlation with cinnarizine solubilization during in vitro lipolysis. *Pharm Res*. 2013;30(12):3101-3113. doi:10.1007/s11095-013-1145-x.
40. Pouton CW. Self-emulsifying drug delivery systems: assessment of the efficiency of emulsification. *Int J Pharm*. 1985;27(2-3):335-348. doi:10.1016/0378-5173(85)90081-X.
41. Shahba AA, Mohsin K, Alanazi FK. Progress in oral drug delivery systems: formulation strategies. *Drug Dev Ind Pharm*. 2013;39(1):1-15.
42. Dorsey PJ, Lau CL, Chang TC, Doerschuk PC, D'Addio SM. Review of machine learning for lipid nanoparticle formulation and process development. *J Pharm Sci*. 2024;113(12):3413-3433. doi:10.1016/j.xphs.2024.09.015.
43. Ros H, Chan N, Cook MT, Shorthouse D. Artificial intelligence and machine learning guided optimization in drug delivery. *Adv Drug Deliv Rev*. 2026;232:115781. doi:10.1016/j.addr.2026.115781.
44. Patel S, Kalasariya A, Desai J, Patel M, Patel A, Shah U. Machine learning-based prediction of drug solubility in lipidic environments: the Sol_ME tool for optimizing lipid-based formulations with a preliminary apalutamide case study. *AAPS PharmSciTech*. 2025;26(2):50. doi:10.1208/s12249-025-03051-5.
45. Shen C, Zhang M, Lu M, Chang E, Gao Z, Ban W, et al. Machine learning empowered formulation design, optimization and characterization of nanoparticulate drug delivery systems: current applications, challenges, and future perspectives. *Acta Pharm Sin B*. 2026;16(2):665-685. doi:10.1016/j.apsb.2025.12.011.
46. Kadian R, Nanda A. A comprehensive insight on self emulsifying drug delivery systems. *Recent Advances in Drug Delivery and Formulation: Formerly Recent Patents on Drug Delivery & Formulation*. 2022 Mar 1;16(1):16-44.
47. Singh V, Sharma V. Artificial Intelligence-Assisted Drug Delivery Systems: From Formulation Design to Personalized Therapeutics. *International Journal of Health Advancement and Clinical Research (tz)*. 2026 Sep 22;4(3):11-9.