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A survey of handwriting synthesis from 2019 to 2024: A comprehensive review

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ABSTRACT

Handwriting, as a uniquely human skill, contributes to fine motor development and cognitive growth. Beyond mere functionality, handwriting carries individuality and subtle emotional nuances, evoking feelings of intimacy and authenticity. Consequently, the generation of synthetic handwritten manuscripts should not only prioritize the production of legible text, but also seek to enhance personalization and authenticity in digital communication. This enhancement renders handwriting synthesis invaluable in domains such as digital marketing and e-learning. Notably, handwriting synthesis plays a pivotal role in forensic science, particularly in signature verification, to bolster security and prevent fraud. Additionally, it has the potential to enhance accessibility, particularly for individuals with disabilities, and assist in health monitoring among elderly populations. Motivated by the significance of handwriting synthesis, this paper conducts a comprehensive literature review on the synthetic generation of handwriting and signatures. By examining research from 2019 to 2024, we categorize methods of synthesis, evaluate synthetic handwriting quality, and explore practical applications. Furthermore, we provide insights into publicly available code resources and emerging synthetic databases.

1. Introduction

Handwritten text synthesis offers diverse practical applications, ranging from personalization of communication through letters, greeting cards, and invitations to facilitating education by providing a comparative tool for children learning to write. Furthermore, its utility extends to forensic science, where it aids in creating handwriting patterns for criminal investigations. Additionally, for individuals with disabilities that impede traditional handwriting [14], such synthesis provides a more intimate means of communication. In the realms of graphic design and art, designers and artists leverage handwritten text synthesis to craft unique and bespoke typography. An example is seen in development of fonts for languages with extensive character sets, such as Chinese and Japanese [103,111].

Another relevant benefit is that handwriting synthesis avoids the need to collect real data from humans, which is a time-consuming and costly method requiring payment of the human collector, at a minimum. Human involvement may introduce labelling errors, including inaccurate data tagging. Furthermore, handwriting is subject to regulations due to its sensitive nature. For instance, data protection laws such as the European General Data Protection Regulation (GDPR) and the American Data Privacy and Protection Act (ADPPA) [1,85] require that companies neither collect nor share information without explicit consent.

While handwriting synthesis is versatile, we must be cautious to prevent its misuse for forging human handwriting. This highlights how important it is to think about ethics and privacy when we use it.

As regards enhancing security, Handwriting Recognition Systems (HRSs) are intended to safeguard access to information by requiring correct recognition. One traditional approach for training these systems involves using synthetic data [108]. Such data help address challenges faced by recognizers, such as effectively distinguishing between genuine handwriting and forgeries. These systems also usually learn to recognize and convert diverse handwriting styles into typed text, which can be quite challenging due to the intra-personal variability of individuals. By leveraging synthetic data, researchers can augment the training process and improve the overall performance of handwriting recognizers.

We note that several relevant surveys have been published on this topic, including contributions from before 2019 [12,32,35,37]. Among the most recent related works, we have identified the following review articles. In [108], handwriting data augmentation in offline mode was reviewed, while various deep learning algorithms for generating handwriting from a given text were studied in [82]. Additionally, a paper

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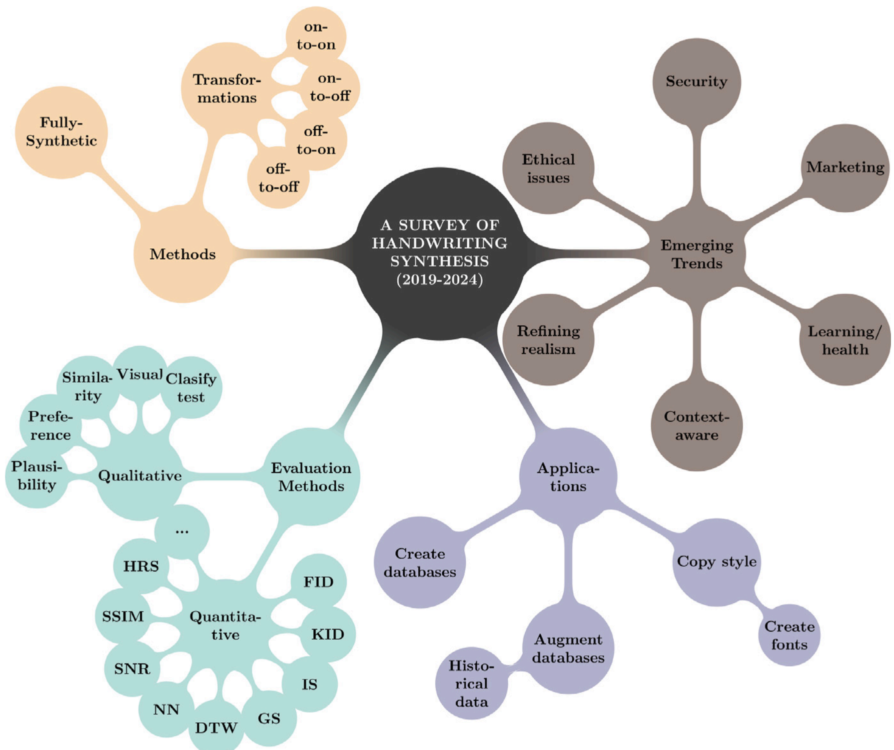


Fig. 1. Overview of the organizational structure of the handwriting synthesis survey.

on generic data synthesis [10] focuses on data generation models in general, with five out of 518 references specifically dedicated to handwriting. Moreover, the articles [36,72] focus on generative adversarial networks (GANs). While the former is dedicated to offline handwriting generation, the latter is more general and mentions handwriting as one of the image application domains. It can be seen that extensive research in data-driven generative methods has significantly contributed to the field of handwriting, particularly in image generation. Considering these circumstances, we propose a new, updated survey that also includes rule-based or model-based generative methods, considers online synthesis, and explores diverse modalities of duplication, as well as applications and types of handwriting synthesis.

To achieve this goal, we have focused on proposals published in the last six years, specifically between 2019 and 2024. As depicted in Fig. 1, our survey methodology is divided into different synthesis methods. On one hand, we explore transformations between online and offline handwriting; on the other hand, we investigate approaches that synthesize new identities without prior style information. The literature analysed presents various evaluation methods, categorized into quantitative and qualitative approaches, as shown in Tables 2 and 3. Finally, the authors have identified several benefits of using synthetic handwriting across a wide range of applications, including copying styles from one text to another, creating realistic fonts, human-like data augmentation, and developing entirely new synthetic handwriting databases. Both synthesis methods and applications are summarized in Table 1.

1.1. Bibliometric and statistical analysis

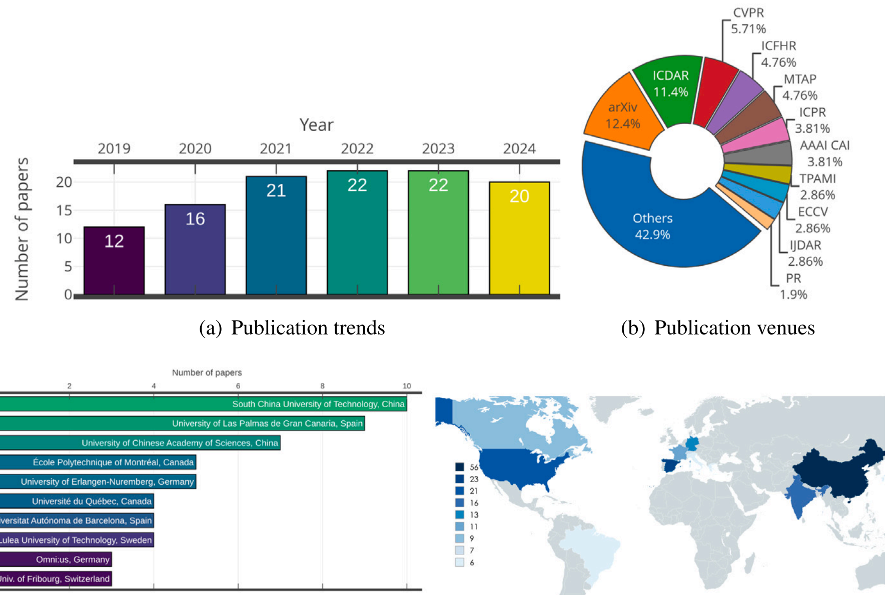
This section presents a bibliometric analysis of articles published between 2019 and October 2024 on the synthesis of handwriting, covering both online and offline methods. The analysis outlines the search strategies and inclusion criteria employed in this survey, along with statistics that reveal trends and patterns.

We conducted two types of searches during the identification stage. Firstly, we looked for papers citing key contributions [7,14,23,64]. Secondly, we retrieved articles from academic databases, including Scopus, IEEE Xplore, and Google Scholar. The search used keywords such as "handwrit* representation", "handwrit* generation", "synthe* handwrit*" and "handwrit* text generation".

We then excluded papers containing terms like "recognition" and "verification", unless they also included one of the specified keywords. Additionally, proceedings from the International Conference on Document Analysis and Recognition (ICDAR) were given special consideration as inclusion criteria. The final sample was refined by removing duplicate papers and those not directly relevant to handwriting synthesis, based on their titles and abstracts.

After this screening process, a total of 110 studies published in journals and conference proceedings between 2019 and 2024 were included in the survey.

Fig. 2(a) shows the number of articles published each year on handwriting synthesis over the six-year period of interest. The data indicate a relatively stable number of publications in later years, averaging around 20 articles per year. Fig. 2(b) highlights the main venues – both international conferences and journals – where these studies have been published. Notably, ICDAR is the most preferred venue for authors in this field. Interestingly, only two editions of the International Conference on Frontiers in Handwriting Recognition (ICFHR) fell within this period, as it is held biennially in even years, with the latest edition in 2022. Despite this limited occurrence, ICFHR ranks third, accounting for 4.76% of the articles. The "others" label includes numerous venues, each publishing one or, at most, two articles, such as TIFS, SNCS, NCAA, ECCV, and IGS, among others. This statistical overview highlights that handwriting synthesis remains a relevant and engaging topic in academia, with findings regularly published in leading journals and conferences. Fig. 2(c) shows the institutions with the highest contributions to handwriting synthesis research, with the South China University of Technology ranking first. Fig. 2(d) shows that China, Spain, and the USA are the top three most active countries based on the works analysed in the survey, with the legend in the figure indicating the number of papers per country. These insights can be valuable for researchers seeking international collaboration by



(a) Publication trends (b) Publication venues

(c) Top publishing institutions (d) Leading publishing countries

Fig. 2. Overview of publication statistics. **(Top-Left):** Number of papers included in this survey. **(Top-Right:)** Main venues where these papers have been published. **(Bottom-Left):** Top 10 universities and research centers with the most published articles. **(Bottom-Right):** Countries with the highest number of publications.

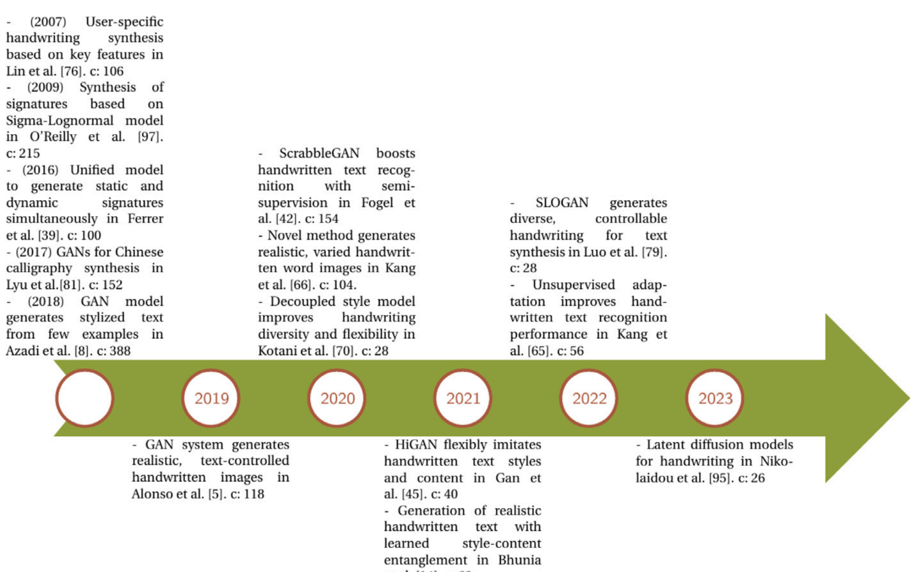


Fig. 3. Timeline illustrating key developments and milestones in handwriting synthesis research, highlighting major contributions and advancements over the years. The letter *c* refers to the number of citations according to Google Scholar, as of November 2024.

identifying the most active institutions.

On the other hand, Fig. 3 shows an evolution timeline of handwriting synthesis in recent years, highlighting key milestones. It also includes some of the significant works prior to 2019 [8,41,76,81,97], providing context for the novel contributions. The works represented in this timeline are connected to the seminal articles identified in Fig. 5.

The remainder of the article is structured as follows: Section 2 presents a classification based on synthesis methods. Section 3 reviews evaluation methods for synthetic data, and Section 4 analyses applications for the synthesis generated. We describe publicly available codes in Section 5, emerging trends in Section 6, and conclude the paper in Section 7.

2. Handwriting synthesis methods

Several techniques are used for generating online or offline synthetic handwriting, such as mathematical models, statistical rules, or generative algorithms that aim to design human-like samples. We identify two methods for handwriting synthesis. The first method focuses on transformations between online and offline handwriting, encompassing a total of four possible transformations. These transformations require a prior handwriting sample, which is typically used to maintain the same style and intra-personal variability. The second method involves fully synthetic handwriting generation, creating a new identity from scratch that does not match any real individual. Table 1 provides a summary

Table 1
Handwriting synthesis methods and applications.

Ref	Year	Model	Synthesis	Application	Task
[6]	2023	Artificial Immune System	off to feature	Augment databases	S
[107]	2022	BLP	off-to-off	Augment cyphered databases	R
[65]	2022	GAN encoders, (Visual&Textual)	off-to-off	Augment database	R
[68]	2022	Y-AE	off-to-off	Synthetic Japanese database	R
[83]	2022	Historical Style Transfer GANs	off-to-off	Improving document's quality	R
[105]	2022	GANS and CNN	off-to-off	Augment database of Gurumukhi	R
[50]	2022	cGAN	off-to-off	Augment database of Tibetan	R
[106]	2022	GANs	off-to-off	Augment database of Urdu	R
[126]	2021	GANs	off-to-off	Augment databases	S
[86]	2021	PSO, Gaussian filter, duplicator	off-to-off	Augment databases	S
[4]	2023	Unconditional GANs	off-to-off	Augment databases	S
[119]	2022	GAN, transformers & FDF	off-to-off	Augment databases	R
[53]	2023	SinGAN	off-to-off	Augment databases	S
[27]	2021	CNN	off-to-off	Augment databases	R
[80]	2020	Fiducial points	off-to-off	Augment databases	R
[62]	2020	GANs	off-to-off	Augment databases	R
[5]	2019	GANs	off-to-off	Augment databases and copy style	R
[132]	2023	Diffusion models	off-to-off	Augment databases and copy style	R
[56]	2019	DCGAN	off-to-off	Synthetic Bangla database	W
[18]	2024	MLS	off-to-off	Augment databases in Arabic	R
[48]	2021	Afine y elastic transformations	off-to-off	Augment databases in Indic scripts	R
[128]	2021	Local variations	off-to-off	Augment databases in Mongolian	R
[92]	2022	CDCGAN	off-to-off	Augment databases in Arabic	R
[9]	2024	Transformer architecture	off-to-off	Augment historical databases	R
[116]	2021	CycleGAN	off-to-off	Augment historical databases	R
[109]	2022	GANs	off-to-off	Augment historical databases	R
[100]	2019	CycleGan and NST	off-to-off	Augment historical databases	R
[58]	2022	Encoder	off-to-off	Copy artistic style	R, W
[14]	2021	Transformer Encoder–decoder	off-to-off	Copy styles	R, W
[45]	2021	GANs	off-to-off	Copy style	R, W
[46]	2022	GANs	off-to-off	Copy style	R, W
[99]	2023	Transformer encoder–decoder	off-to-off	Copy style	R, W
[42]	2020	GANs with HRS	off-to-off	Copy style	R, W
[66]	2020	GANs with encoders of style	off-to-off	Copy style	R, W
[114]	2024	VATr	off-to-off	Copy style	R, W
[124]	2022	cGAN	off-to-off	Copy style in Chinese	R, W
[130]	2020	CNN, msM, cGRU, GMM	off-to-off	Copy style in Chinese.	R, W
[75]	2023	DDPM	off-to-off	Copy styles in chinese	R, W
[28]	2022	Auxiliary Classifier GAN	off-to-off	Synthetic Bangla database	R
[101]	2021	CNN and Autoencoder	off-to-off	Create forgeries to train SVS	S
[87]	2021	GANs with local path loss	off-to-off	Enhance a patches discriminator	R, W
[118]	2019	Cellular automata	off-to-off	Augment database	R
[57]	2024	Denoising diffusion probabilistic model	off-to-off	Augment databases	S
[20]	2022	Perturbations and Bezier curve	off-to-off & off-to-on	Augment databases	R
[117]	2022	CNN and RNN	off-to-off & text-to-HW	Database in old Vietnamese	R
[59]	2021	GANs	off-to-off & text-to-HW	Augment databases	R, W
[34]	2022	CycleGAN, Contrastive Unpaired Translation	off-to-off & text-to-HW	Database of Chu nom characters	R, W
[91]	2024	ViT with a mT5 transformers	off-to-on	Handwritten vectorized notes	R
[120]	2021	Bézier splines	off-to-on	Copy style in Mongolian	R
[7]	2021	CRNN with DTW loss	off-to-on	Copy styles	R, W
[21]	2022	Double Stream Parsing Encoder	off-to-on	recover trajectory	R, W
[55]	2023	CNN with BiLSTM	off-to-on	Recover trajectory	R
[93]	2020	Encoder–decoder and GMM	off-to-on	Stroke trajectory recovery	R
[94]	2020	Encoder–decoder and GMM	off-to-on	Stroke trajectory recovery	R
[131]	2019	CNN	off-to-on	Stroke trajectory recovery	R
[102]	2024	Autoencoder with attention model	off-to-on	Stroke trajectory recovery (scripts)	R
[30]	2022	Heuristic rules	off-to-on	Signatures trajectory recovery	S
[88]	2020	Iterative knowledge transfer	off-to-on, on-to-on & on-to-off	Copy style	W
[33]	2019	Enhanced image generation	on-to-off	Medical application.	W
[90]	2019	FCN	on-to-off	Augment databases	S
[49]	2020	SC-GAN	on-to-off	Augment databases and copy style	R, W
[60]	2019	Handwriting synthesis pipeline	on-to-off	Copy style	R, W
[64]	2022	Sigma-lognormal and Stroke-cCycleGAN	on-to-off & off-to-off	Augment databases	S
[113]	2021	Sequential VAE	on-to-on	Augment database	R
[73]	2022	Sigma-lognormal and 1D CNN	on-to-on	Augment databases	S
[19]	2022	Controllable generative model	on-to-on	Augment databases	R, W
[63]	2019	GANs	on-to-on	Copy style	R
[70]	2020	DSD	on-to-on	Copy style and create new	R, W
[103]	2023	Conditional DDPM	on-to-on	Copy style in Chinese	R, W
[112]	2021	Encoder–decoder.	on-to-on	Copy style in Chinese	R, W
[23]	2019	POMH	on-to-on	Research new representation	R, S
[11]	2020	HMM	on-to-on	Research new representation	R

(*continued on next page*)

Table 1 (*continued*).

[110]	2023	TCN	on-to-on	Stroke trajectory reconstruction	R
[25]	2023	SDT	on-to-on & off-to-off	Copy style	R, W
[39]	2019	Sigma-lognormal	on-to-on & on-to-off	Augment databases with forgeries	S
[104]	2020	Rules on the signatures' shape.	fully synthetic	Augment database for forgeries	S
[79]	2023	GANs	text-to-HW	Augment databases	R, W
[71]	2022	RNN	text-to-HW	Copy style	R, W
[122]	2021	Autoencoder&character generator	text-to-HW	Create dataset	R
[15]	2017	Rules on characters	text-to-HW	Create dataset	R, W
[67]	2020	Pixel deformations	text-to-HW	Create dataset	R
[95]	2023	Latent Diffusion Model	text-to-HW	Create style & content	R, W
[111]	2022	SAM & self-reconstruction branch	text-to-HW	Create handwritten type fonts	R, W
[13]	2024	Rules on characters	text-to-HW	Create type fonts in Gujarati	R, W
[77]	2024	Image and sequence synthesis	text-to-HW	Create new fonts in Chinese	R, W
[24]	2019	Sinusoidal model	text-to-HW	Create the velocity of handwriting	R
[17]	2020	DM-Font	text-to-HW	Create typewriting fonts	R
[69]	2022	CAM	text-to-HW	Create typography	R, W
[74]	2020	cGAN	text-to-HW	Create handwriting from text	R, W

Note. The abbreviations in the table are: Parsimonious oscillatory model for handwriting (POMH); Artificial Immune System (AIS); Particle Swarm Optimization (PSO); Style Aggregation Module (SAM); Variational Autoencoder (VAE); style-disentangled Transformer (SDT); Denoising Diffusion Probabilistic Models (DDPM); Decoupled Style Descriptors (DSD); feature deformation fusion (FDF); Visual Archetype Transformer (VATr); Cellular Automata Learning and Prediction (CALP); Y-Autoencoder (Y-AE); Neural Style Transfer Algorithms (NST); Vision Transformer (ViT); style-conditioned GAN (SC-GAN); Deep convolutional GAN (DCGAN); Bidirectional Long Short-Term Memory (BiLSTM); Moving Least Squares (MLS); Conditional Deep Convolutional GANs (CDCGAN); Component aware module (CAM); Temporal Convolutional Network (TCN); Bayesian Program Learning (BPL); Dual memory-Augmented Font Generation Network (DM-Font). The "Task" column includes: R (handwriting recognition), W (writer authentication based on handwritten documents), and/or S (writer authentication based on signatures).

of research papers categorized by these methodologies.

2.1. Handwriting transformations

Data-dependent synthesis typically utilizes two, and occasionally three, existing handwriting samples: online, offline, and sometimes a vectorized format. The objective is to convert handwriting from one modality to another. This leads to identifying four distinct subcategories of data conversion: *on-to-on, on-to-off, off-to-on,* and *off-to-off*. Each subcategory is detailed in the following respective subsections, providing insights into the methodologies for each type of data transformation.

2.1.1. On-to-on

This transformation is frequently observed in the literature. In these scenarios, researchers begin with online handwriting and manipulate attributes such as velocities and trajectories to introduce realistic human-like distortions. These modifications are achieved through perturbations which can take the form of mathematical expressions or can be integrated into the core of deep-learning architectures [70, 73]. Examples of mathematical perturbations include bivariate Gaussian and Bernoulli distributions, and models such as sinusoidal or sigma-lognormal [40].

Synthesizing natural human movements using sinusoidal oscillations is investigated in [23]. The authors examine the relationship between velocities in the vertical and horizontal movements and the traces. Later, a multi-component sinusoidal model was applied to correlate this information.

Another mathematical approach involves the Sigma-Lognormal model used by [39], which simulates realistic features of strokes and then distorts them. In [73] the model facilitates signature augmentation for a signature verifier that does not require any training with forgeries, implemented through a self-supervised learning framework. This model was employed in [113] to segment the traces into strokes, which are then processed through a Variational Autoencoder (VAE) to augment databases.

Further research involves developing handwriting synthesis for Chinese and other languages [25]. To do this, a "style-disentangled Transformer" separates the writer's style and character style. Conditional Denoising Diffusion Probabilistic Models (DDPMs) are utilized by researchers in [103]. The character is obtained starting with random Gaussian noise followed by the reverse process through denoising. Also, in Chinese, an encoder–decoder architecture was used in [112].

Moreover, [70] proposed a method of Decoupled Style Descriptors (DSD) to generate variations of the writer's style, character style, and writer-character, to give a character that still depends on the writer. An alternative approach is seen in [71], which involves using a Long short-term memory network (LSTM) to use its long-term dependency, which is useful for teaching through reinforced learning.

Other noteworthy methods include the use of Generative Adversarial Networks (GANs) [63] to create a realistic imitation of the input handwriting. A database with human handwriting was developed in [63], processing it through the Temporal Convolutional Network (TCN) to reconstruct trajectory traces. Lastly, Hidden Markov Models (HMMs) and progressive iterative approximation to enhance handwriting synthesis and classification were applied in [11].

2.1.2. On-to-off

This transformation involves converting online trajectories, which may be either synthesized or real, into offline images. Before the transformation, some researchers used to augment the quantity of online data to subsequently convert them into offline handwriting, thus increasing the number of samples available.

This transformation was explored in [49] with paired data (online samples that have been simultaneously registered alongside an offline sample). The authors used the skeleton of the online and an offline image previously encoded as style to get the new offline data. Similarly, [90] also employed paired data to train the Fully Convolutional Neural Networks (FCNNs). By inputting online data and forcing the real offline output in the training stage, the network can learn how it is made. This is used to augment offline databases for handwriting or signature verification. In contrast, however, a method for transforming data without paired data was developed in [64]. To achieve a better outcome, the authors created a system to achieve different stroke widths, to make it match human handwriting more precisely.

In [60] the researchers replicated the writer's style in an offline specimen by rendering the online handwriting with random perturbations. [33] investigated the use of this transformation to augment databases for early diagnosis and monitoring of neurodegenerative disorders, especially Parkinson's disease, employing the VGG16 architecture, a Convolutional Neural Network (CNN). Meanwhile, offline and online generation of signature forgeries using the sigma-lognormal model was proposed in [39], obtaining on-to-off and on-to-on transformations.

Other proposals make use of this transformation after creating an off-to-on transformation [7,88]. In this way, they approach an augmentation scheme that avoids the use of direct off-to-off transformations.

2.1.3. Off-to-on

This transformation represents the most challenging category among all transformation types. The aim is to reconstruct online trajectories from offline images. Given the complexity of this task, many studies do not fully achieve the intended online data synthesis. This review will therefore include those efforts that approximate online handwriting, achieving outcomes such as the vectorized format or stroke recovery.

A Convolutional Recurrent Neural Network (CRNN) was employed in [7] to predict subsequent coordinates based on the previous position. The authors employed Dynamic Time Warping (DTW) to align predictions and ground truth points [7]. This method addresses variations in stroke order and direction, such as the sequence in which a person dots an "i" or crosses a "t". The trajectory that best fits the DTW score is selected iteratively. Initially, the CRNN is trained using paired data. This approach also facilitates an on-to-off transformation.

The study in [102] introduces an autoencoder with an attention model for recovery of pen-up and down, velocity, and temporal order. The authors extracted features and the vectors are decoded to produce the online data.

An off-to-on transformation was executed in [88], followed by an on-to-on transformation of a reference to augment samples. Finally, the authors execute an on-to-off transformation to mimic a writer's style using only a single line of text. This demonstrates that subdividing the information enhances feasibility.

Methods for converting offline Japanese kanji into online were investigated in [93,94]. This task is particularly challenging due to the complexity of kanji characters and the multitude of possible stroke orientations.

In [21] the authors recover the trajectory of the handwriting through a double-stream parsing encoder, which is two CRNNs, one in each axis, and a Bidirectional LSTM (BiLSTM) that analyses the relation between the strokes. A BiLSTM was also used in [55] to predict recovery coordinates using DTW, coupled with a chamfer distance loss function to achieve an improved similarity score. Subsequently, [54] further applied this transformation to replicate the style in an on-to-on transformation.

Converting handwriting images into digital ink, specifically in vector form, was proposed in [91]. The authors derender the images and extend a Vision-Language Model (VLM). This model first learns to read, and then localizes the text in the image, to then translate it and extract the textual elements. Their achievements can be viewed online.[1]

2.1.4. Off-to-off

This transformation is extensively researched within the field of handwriting synthesis. Researchers begin with offline handwriting images and they then train models to produce further synthetic images. The primary purpose is often to replicate styles [14,25,42,46,65,99,124,130], though augmenting databases remains a challenging goal [27,48,52,53,86,101,126].

This type of transformation usually employs various perturbations. Common techniques include affine (rotation, scaling, translation, stretching), colour, blur, brightness, and contrast augmentation [48]. More advanced distortions involve random masking with noise and techniques such as hide and seek, which randomly erase parts of the image [20]. Other innovative approaches include Moving Least Squares (MLS) [18], which modifies small sections to augment further data; manipulating fiducial points in the bounding box to distort the image [80]; and employing Cellular Automata Learning and Prediction (CALP) [118] rules to transform images through evolution until they become unrecognizable. You can also embed rules into a deep-learning architecture. A recent study in [115] empirically demonstrated the effectiveness of utilizing data inverted in comparison to the original signature images for training a SigNet model [51].

Prominent methods in this area include the work of Alonso et al. [5]. The authors employ a modified GAN and BiLSTM to research data generation with any content to achieve a better HRS. Following this, ScrabbleGAN [42] synthesizes handwriting in varying lengths and styles using a semi-supervised GAN, combining a discriminator to ensure the plausibility of the handwriting and a text recognition network for readability. HiGAN+ [46], an advance on HiGAN [45], uses patches to arrange letters sequentially, learning superpositions and transitions between them.

GANwriting [66] is another significant contribution, designed to produce realistic handwriting with authentic textual content and distinctive styles. It includes interpolation between styles, enabling synthesis of styles not written by a human. To further develop this work, in [87] the authors create a patch discriminator called "SmartPatch". Furthermore, in [119] the authors research methods to enhance the model's capabilities by adding punctuation marks and other unusual symbols.

In Handwriting Transformers [14] the authors employ an encoder–decoder architecture to mimic styles in any desired length of text. Subsequently, in [99] the authors use this method to enhance handwriting resemblance to the original and generate symbols and glyphs not written by the author of the original style. Dai et al. [25] also adopted their style-disentangled Transformer to achieve an off-to-off transformation.

Additional research focuses on stylized handwriting for specific languages. In [124] the authors use a conditional GAN (cGAN), enhancing the base loss functions of GANs to emulate the style of handwriting in Chinese. In [130] a CNN architecture is employed to extract the calligraphy features in Chinese, supported by a mata-style Matrix (msM) and a calligraphy-clustering attention module.

Finally, several studies aim to enhance historical HRSs. These involve acquiring sets of historical documents and augmenting them while maintaining the original handwriting style. Techniques used include CycleGAN and Neural Style Transfer (NST) algorithms [100]; CycleGAN and adding Gaussian Noise to the image [116]; LineGen (a GAN) with a spacing network to obtain a better stroke width [109]; and Historical Style Transfer GAN (HST-GAN), which also enhances the quality of documents [84]. Other approaches include transformer-based architecture [9] and a CNN and a Recurrent Neural Network (RNN) [117]. The latter obtains old Vietnamese synthetic documents.

2.2. Fully synthetic handwriting creation

Fully synthetic handwriting synthesis, also known as text-to-handwriting (text-to-HW), does not require human handwriting samples as input. This method involves either keyboard text entry or random words for subsequent conversion into human-like handwriting with a synthetic style. This synthesis is carried out using rules. The rules can be human-devised, based on approximations and assumptions, or derived through machine learning, mainly using deep-learning architectures.

In [122] the synthesis process involves writing rules for each letter. The rules dictate points that are then connected either by a Bézier curve or a straight line. To introduce variability and mimic inaccuracies in human handwriting, modifications include random alteration of point positions, irregular tracing, and the removal of some pixels to simulate scanning errors. Similarly, these rules were employed in [15], but with the addition of another rule for linking letters, facilitating the calculation of velocity profiles. In [104] a set of rules were used to synthesize signatures that do not appear human handwritten.

In [67], fonts that resemble human handwriting are used as a base. Data augmentation techniques are then used to deform those fonts and generate more variability. Those deformations include blurring, gamma, brightness, and contrast adjustments or Gaussian noise for the image's pixel map, and geometric transformations such as shear,

[1] huggingface.co/spaces/Derendering/Model-Output-Playground.

Table 2
Quantitative evaluation methods for the synthesis.

	Evaluating online data	Evaluating offline data
Frèchet Inception distance (FID); Variable-length FID (vFID); LPIPS		[14,42,46,65,66,87,99,114,119]
Kullback–Leibler divergence (KID)		[46]
Handwriting Distance (HWD)		[114]
Inception Score (IS)		[46]
Geometric Score (GS)		[14,42,79,99]
Dynamic Time Warping (DTW); Length-independent DTW (LDTW)	[7,21,24,25,103,110]	
Nearest Neighbour Distance (NN distance)	[7]	[7]
Signal-to-noise ratio (SNR), Peak SNR (PSNR)	[23]	[46,53]
Structural Similarity Index Measure (SSIM); Mean SSIM (MSSIM)		[46,53,53]
Wilcoxon signed ranks test		[6]
Content Score	[25]	
Style Score	[25]	
Compare metrics with other synthesizers	[63,70,71,73,103]	[42,64,79,87,104,111]
Character error rate (CER)/Symbol error rate (SER)/Word error rate (WER)	[19,23]	[46,65,65,79,79,99,119]
Word identification error recognition WIER		[46]
Root Mean Square Errors (RMSE)	[30]	
Equal error rate (EER)	[73]	[86,90,104,113,126]
Detection error Tradeoff (DET)		[90,113]
False Rejection Rate (FRR)/ False Acceptance Rate (FAR)/Recall		[6,101,105,126]
Mean Absolute Error Rates (MAE); Average Error Rates (AER)		[6,77]
Accuracy	[91]	[101,124,128]
Precision		[105]
Levenshtein distance (Edit Distance)		[5]
Character lever F1-score	[91]	[105]

Table 3
Qualitative evaluation methods for the synthesis.

	Evaluating online data	Evaluating offline data
Visual	All	
Preference		[14,25]
Similarity	[70,103]	[88,111]
Plausibility	[24,25]	[14,103]
Turing (*is it real or not?*)		[66,79]

rotation, scaling, and an elastic deformation [67]. Similarly, [121] uses ready-made handwriting-like typewriting fonts to enhance HRSs without annotated data.

In [79], a style bank is created through a database, employing a GAN as a rule to generate text-to-HW. The data is transformed into a feature vector, which can be modified to produce new, non-existent styles of handwriting. This latter possibility is also seen in [19]. The authors aim to augment databases with new content and styles. The model learns a distribution of the samples, enabling generation of new handwriting. A similar objective is pursued in [95] using a conditional Latent Diffusion Model.

Synthesis of typewriting fonts is particularly useful for scripts with complex characters involving many strokes, such as Chinese. In [111], a component tree based on a decomposition table is used to establish the relations between glyphs and styles. [123] employs few-shot information, while [77] recombines features. For scripts such as Korean and Thai [17] a Dual Memory Augmented Font Generation Network (DM-Font) is used, which decomposes the glyphs into components. For Indic scripts such as Gujarati [13], rules were designed for each letter and for concatenation of strokes.

Additional research based on other scripts focuses on augmenting databases. [68] focuses on Japanese, using a Y-Autoencoder (Y-AE) model, which is an encoder with a conditional decoder; the historical handwriting chu nom script, a historical version of Vietnamese, is seen in [34] with a CycleGAN and a Contrastive Unpaired Translation (CUT) with annotation-free training and [117], where the authors, beyond the off-to-off transformation, also obtained a text-to-HW approach. A multilingual approach is employed in [59], using a GAN to generate handwritten text for multiple languages.

Finally, [58] demonstrated the possibility of extrapolating scene text to handwriting. This process involves an encoder for Destylization which extracts the text style, and a font transfer mechanism that renders the content with the extracted style. Texture is rendered as the final step.

3. Evaluating the quality of synthetic handwriting

Assessing handwriting makes it possible to ensure that the generated samples align with the intended objectives. Various evaluation techniques, both established and newly developed [21,65,114], are suggested for this purpose. Researchers employ two primary types of evaluation: quantitative and qualitative. Tables 2 and 3 summarize the evaluation methods identified in the reviewed literature, facilitating selection of suitable methods for both online and offline handwriting.

3.1. Quantitative evaluation

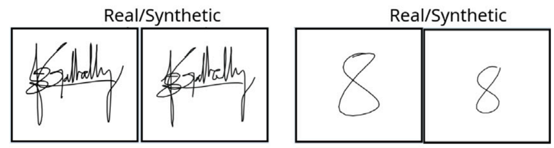
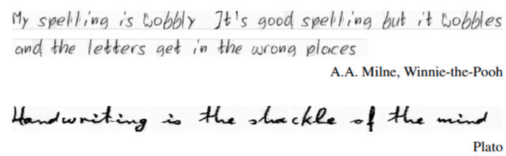
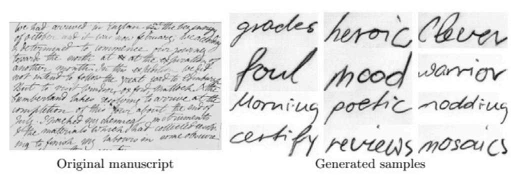
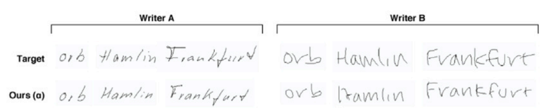
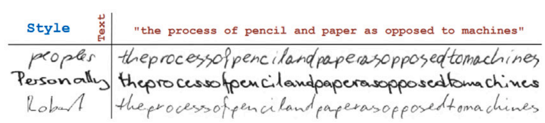
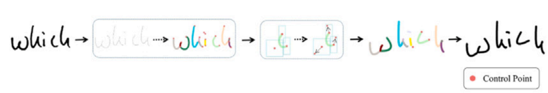
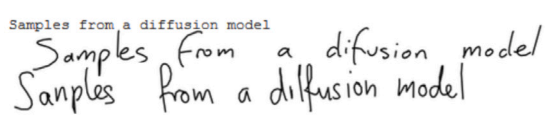
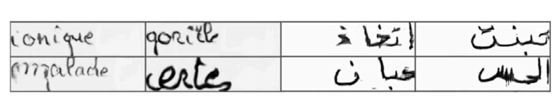
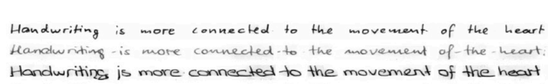
Fréchet Inception Distance (FID) is widely used to measure the distance between the feature vectors calculated for real and synthetic images [77]. An enhanced version of variable-length FID (vFID) [65] evaluates images of variable lengths. LPIPS is similar to FID, expressed as a percent [77]. Kullback–Leibler Divergence (KLD) measures the divergence between real and synthetic images [46]. The Handwriting Distance (HWD) assesses the calligraphic distance between real and synthetic handwriting [114]. Inception Score (IS) evaluates the realism and diversity of generated images [46]. Geometric Score (GS) compares the image topology of both original and synthetic writing [5].

Dynamic Time Warping (DTW) calculates the distance between the real and synthetic character for online evaluation [25]. DTW was adapted for length-independent comparison (Length-independent DTW (LDTW)) [21] and alignment [110]. Nearest Neighbour distance (NN distance) measures the proximity between predicted and actual points [7].

The Peak Signal-to-Noise Ratio (PSNR) compares the maximal signal power to the distorting noise power in images, and is used to assess the quality of a genuine and augmented image [53]. The Structural Similarity Index Measure (SSIM) and Mean SSIM (MSSIM) is a model that considers the change in the image structure as a degradation [46, 53]. Wilcoxon signed ranks assess the statistical performance of the system [6]. Content Score and Style Score measure the accuracy of content generation and style similarity, respectively [25].

Researchers also use recognition and verification systems to confirm that the synthesis is readable, as well as Optical Character Recognition (OCR) or verification systems to be sure that the augmentation scheme

Table 4
Some examples of advanced methods in duplication and fully synthetic generation, with visual results of synthetic samples. *Figures obtained from the cited articles in the left column.*

Duplication				Fully synthetic			Visual example of the outputs
on2on	on2off	off2off	off2on	on	off		
●	○	○	○	○	○	DeepWriteSYN generates realistic long&short-term handwriting variations using deep learning, improving flexibility and enhancing one-shot learning in signature verification [113].	
○	○	●	○	○	○	ScrabbleGAN is a semi-supervised generative model for synthesizing offline handwritten text images by assembling character images, enabling versatile styles and lexicons, boosting HTR performance with enriched training data and semi-supervised learning [42].	
○	○	●	○	○	○	This method generates realistic, varied handwritten word images by conditioning on style and content, using a multi-cue approach for calligraphic styles in a few-shot setup [66].	
●	○	○	○	○	○	The model decouples style factors in online handwriting synthesis, improving stroke generation, interpolation, and writer identification, with potential for other sequential data tasks [70].	
○	○	●	○	○	○	HiGAN is a generative model that mimics handwriting styles, generating realistic, variable-length handwritten texts conditioned on arbitrary content and styles, improving scalability and quality [45].	
○	●	●	○	○	○	Method for generating realistic offline signatures from online specimens, enhancing verification without skilled forgeries and improving handwriting signature verification performance [64].	
○	○	○	●	○	○	A script-level off-to-on handwritten text augmentation method using Bézier curves, enhancing character recognition performance by generating more diverse samples compared to holistic augmentation techniques [20].	
○	○	○	○	●	○	Diffusion probabilistic model for handwriting generation, simplifying training and producing realistic, high-quality text images without adversarial or writer-recognition objectives [78].	
○	○	○	○	○	●	The method generates synthetic handwritten word images using an adversarial model, improving recognition with added synthetic data [5].	
○	○	○	○	○	●	SLOGAN synthesizes controllable, diverse handwriting styles for arbitrary-length, out-of-vocabulary text using a GAN, enhancing text recognition with parameterized style and content embedding [79].	

works. Through this, they use numerous error metrics. Character Error Rate (CER), Symbol Error Rate (SER), and Word Error Rate (WER) are for readability [46] and Word Identification Error Rate (WIER) is the number of times the system confounds the writer [46].

Other popular metrics are the Root Mean Square Errors (RMSE), which calculates distances between two sequences [30]; or the Equal Error Rate (EER), that is the point in the Detection Error Tradeoff (DET) curve where the False Acceptance Rate (FAR) equals the False Rejection Rate (FRR) [90,126]. Other errors are Mean Absolute Error (MAE), which measures the absolute differences between the predicted and the ground truth values [77], and Average Error Rates (AERs) [6].

Other measures related to recognition and verification systems are Word Recognition Accuracy to evaluate the quality of the augmented samples [124,128] and Recognition Exact Match Accuracy to assess the

Table 5
Quantitative comparison of prior works on offline handwritten text synthesis.

Method	FID↓	GS↓
Alonso et al. [5]	23.94	$8.58 \cdot 10^{-4}$
ScrabbleGAN [42]	23.78	$7.60 \cdot 10^{-4}$
Bhunia et al. [14]	19.40	$1.01 \cdot 10^{-2}$
HiGAN [45]	17.28	–
HiGAN+ [46]	5.95	–
Wordstylist [95]	18.58	$2.85 \cdot 10^{-2}$
SmartPatch [87]	49.00	–
SLOGAN [79]	12.06	$5.59 \cdot 10^{-4}$
One-DM [26]	15.73	$1.98 \cdot 10^{-3}$

Table 6
Quantitative comparison of off-to-off duplication methods.

Method	DB: IAM		DB: RIMES	
	WER↓	CER↓	WER↓	CER↓
Alonso et al. [5]	–	–	11.90	4.03
Zhang et al. [129]	22.20	8.50	–	–
Fogel et al. [42]	23.61	13.42	11.32	3.57
Kang et al. [65]	26.69	8.62	–	–
Kang et al. [67]	17.26	6.75	–	–
Nikolaidou [95]	21.93	8.80	–	–
Mattick [87]	65.25	36.63	–	–
Luo [79]	12.90	4.94	8.80	2.44

semantic consistency and geometric properties [91], which are Accuracy metrics (ACC), the percentage of accurate projections [105]. Recall is the percentage of true positives [105], while precision is a percentage of correctly affirmative identification. Adaptative Intersection of Union (AIoU) is a metric on the fidelity of the glyph [21]. Levenshtein distance at the character level (Edit Distance) is used to measure the impact of data augmentation on text recognition performance [5]. Character Level F1 score measures geometry and semantics by counting the character bounding boxes [91].

3.2. Qualitative evaluation

As shown in Table 3, qualitative evaluation relates mainly to human inspection. Visual inspection is used universally to verify the intended outcome. Then there are some tests. Firstly, some human participants are found. In some cases, diversity of opinions is sought, even without any previous experience. In other cases, people experienced in style recognition are sought [79]. After that, they are provided with some real samples and some synthetic samples. There are then multiple possibilities: a preference study (to determine preferences for synthetic or real handwriting [14]), a classification test (to recognize authenticity [28]), and a plausibility study (to assess human-like accuracy of the synthetic handwriting [14]). To compare different models, these methods help ascertain whether one model performs better in specific aspects [14,64].

Finally, additional visual comparisons are included in Table 4 to further enhance understanding of the practical improvements made by several methods. A description of the key findings from the various works is provided along with the visual examples.

3.3. Quantitative analysis of the quality of synthesized handwriting

In handwriting synthesis, the state of the art remains unclear. One reason is that synthesis is often conducted for specific applications, such as style replication, database augmentation, system training enhancement, trajectory recovery, and other purposes. The absence of common benchmarks and international competitions in handwriting synthesis sometimes makes it challenging to compare results fairly across different works. Nevertheless, in this section, we present a quantitative evaluation of some studies that have addressed specific challenges.

Table 5 presents a comparative analysis of handwritten text synthesis using the FID and GS similarity metrics. It is worth mentioning as a positive aspect that FID effectively evaluates the visual similarity between real and synthetic handwriting by capturing high-level features. However, its limitation lies in being image-focused, potentially overlooking geometric or trajectory-specific details crucial in handwriting. In contrast, GS focuses more on the structural and spatial accuracy of handwriting, making it well-suited for geometric comparisons, but it lacks the ability to assess the overall perceptual quality of images as effectively as FID.

Another important comparison involves handwriting duplication. Although various methods have been proposed, Table 6 compiles works that evaluate their performance under similar training conditions in the case of off-to-off. In this case, dissimilarities are quantified using WER and CER. While WER measures the error rate at the word level, CER is based on a normalized Levenshtein distance.

With regard to these metrics, we first note that FID and GS are the most commonly used for comparing synthetic and real handwriting in offline settings. Similarly, CER and WER are the most popular metrics for evaluating duplication strategies in offline handwriting.

When the task to be solved is signature verification, we observe that augmenting the training set with offline duplicates also serves as a way to validate the synthesis methods. Table 7 shows some results with different signature databases and metrics. EER is more appropriate for both research and benchmarking when comparing different methods, as it balances the two types of errors (FRR and FAR) in Detection Error Tradeoff (DET) curves. However, in certain security applications, such as border control, EER might not be the most suitable operating point. ACC is better for deployment-focused evaluations where specific thresholds are fixed, although it is not commonly used in the field and does not balance FAR and FRR.

In online handwriting synthesis, clear evaluations of real versus synthesized samples are less commonly observed. For instance, in signature verification, synthetic signatures are frequently employed to improve automatic verification systems. An example is provided in [73], where applying lognormal-based synthesis improves the EER (%). A similar evaluation approach is found in [23], where a synthesis method is assessed using the Signal-to-Noise Ratio (SNR) to compare the similarities between real and reconstructed velocities. Additionally, synthetic online data has proven effective in a word recognition challenge, where performance was evaluated in terms of CER.

In the off-to-on modality for duplicating handwriting, the DTW and RMSE metrics are among the most widely used across multiple studies. Table 8 summarizes several reviewed articles that employ these common metrics. However, the comparisons are not entirely fair, as the experimental protocols and databases used often differ. Using RMSE is more suitable when accuracy in exact pointwise values is critical, and the sequences are well-aligned. In contrast, DTW is more appropriate when the lengths of sequences vary, although it tends to penalize errors more heavily during trajectory recovery.

4. Applications in the field of synthetic handwriting

An overview of Table 1 reveals that the most common application of handwriting is data augmentation, which contributes to creating a more robust handwriting or signature verification system. Researchers have highlighted the limitations of existing databases, noting that they are a costly method and not sufficiently extensive. By augmenting the samples of intra or inter-personal signatures or handwriting, these systems are expected to deliver improved accuracy and reduced error rates [4,86,104,127].

A specific case of augmenting databases is presented in [6]. In this case the research was focused on augmenting the databases for a signature verifier that requires only signature features. So, the authors synthesized offline signatures into feature sets and then modified them. In [86], a PSO-based hyperparameter optimization method was

Table 7
Quantitative comparison of off-to-off methods in offline automatic signature verification.

Method	#Tr. Sig.[a]	DB: CEDAR		DB: UTSig		DB: GPDSsynth		DB: MCYT75	
		EER↓	ACC↑	EER↓	ACC↑	EER↓	ACC↑	EER↓	ACC↑
Hong et al. [57]	12	0.0518	94.87%	–	–	–	–	–	–
Hong et al. [101]	22	–	–	–	83.73%	–	–	–	–
Hameed et al. [53]	10	–	–	–	–	–	62.23%	–	–
Al-Suhaibani et al. [4]	10	–	–	0.001	99.61%	–	–	–	–
Maruyama et al. [86]	3	0.82%	–	–	–	0.20%[b]	–	0.01%	–
Yapıcı et al. [126]	10	–	–	–	–	–	–	2.58%	–
Viana et al. [115]	10	2.95%	–	–	–	2.75%	–	2.01%	–

[a] Number of real training signatures per signer.
[b] Result obtained from the real GPDS database.

Table 8
Quantitative comparison of off-to-on duplication methods.

Database	Method	DTW↓	RMSE↓
Signatures	Diaz et al. [30]	3.90	0.23
Handwriting	Chen et al. [21]	77.35	15.12
	Nguyen et al. [93]	109.4	16.05
	Dai et al. [25]	1.61	–

utilized to model writer variability using an offline signature duplicator [31], and was validated using a discriminant feature descriptor from SIGNET-f [51].

The potential to create entire databases of synthetic handwriting has been researched. This approach is particularly useful for generating large-scale databases for training the HRS/HVS/SVS [122]. Although synthetic forgeries can be created for training purposes [104], there is a trend towards using only original data, as synthetic forgeries are challenging to produce authentically [64].

Improving the readability of historical documents through HRS is another significant application. Many historical documents are not easily readable. A robust HRS could translate some documents that humans are unable to understand, after learning using other documents. Once again, strategy for augmenting existing databases is pursued in this field of application to enhance the performance of HRSs [9,34,100,109,116,117]. Furthermore, in historical data, cyphered handwriting is an even more difficult task to approach. In [107], a Bayesian Program Learning was used to handle this task.

Handwriting-aid systems that replicate an individual's handwriting style could be highly beneficial for people with writing impairments [14,87]. This application uses original human data, transforming it to meet specific needs. This is an intensively studied topic that has shown high fidelity in replicating human handwriting. This technique could also support the enhancement of recognition or verification systems, by augmenting the original data.

Occasionally, the focus shifts to acquiring specific handwriting features such as symbols [99] or digits [56,62]. In [99], this function was used to prove that they achieve few-shot transformation, for augmenting databases [62], and for generating specific Bangla digits [56]. In addition to augmenting training data, synthetic data can also be used to test the vulnerability of recognition systems against skilled synthetic forgery attacks [47].

A specialized application is the generation of handwritten typewriting fonts to appear human-written. This process is often targeted at languages with complex character sets such as Chinese [69,111], Korean, and Thai [17] or Indic scripts such as Gujarati [13]. While not extensively researched, this application holds significant potential for artists who wish to incorporate personalized handwriting into their works effortlessly.

The synthesis works on a script, with the majority of research focusing on the Latin script due to its prevalence in the global research community. However, efforts are also being made to synthesize handwriting in other scripts, such as Mongolian [120,128]; different Indic scripts [48] such as Gujarati [13], Bangla [28,38,56], Devanagari [38], Gurumukhi [105]; Chinese [74,77,103,112]; Arabic [18,92,106]; Tibetan [50]; and Cyric [43]. Finally, there is some research on a multilingual approach [59,102]. This research may be important for diversifying views and for obtaining a robust global verification or recognition system. Currently, there appears to be limited research available for many languages.

5. Publicly available codes

Some researchers have extended the accessibility of their work beyond traditional publications by hosting their research output on online platforms. This includes not only their papers but also the source code associated with their studies. Making these resources available online supports the replication of findings, as advocated by the scientific method. It is particularly beneficial for researchers in novel areas who wish to implement these concepts but may lack deep expertise in the specific area. Access to practical examples that are operational enhances their understanding and fosters further scientific inquiry.

The web pages for the publicly available source codes related to the papers reviewed are listed in Table 9, accompanied by brief descriptions of their functionalities.

The table also presents information about new synthetic databases that are now publicly available. On one hand, IHR-NomDB is an offline database of synthetic, old, degraded Vietnamese handwritten script. Building on previous works [34,117], this project has produced a total of 704,991 generated character images, distributed across 106,622 text columns. The lexicon contains 13,254 unique ChuNom characters. This database is shared with real images of this language. On the other hand, the offline synthetic database developed in this work [28] consists of handwritten Bangla characters, generated using a modified Auxiliary Classifier GAN model. The authors demonstrated that the generated samples significantly outperform those produced by the basic AC-GAN architecture, according to the FID metric. This database is proposed to advance OCR research, among other domains. Note that prior to this period (2019–2024), other fully synthetic databases emerged, such as online and offline synthetic signatures [41].

6. Emerging trends

After reviewing different recent works in handwriting synthesis, we introduce in this section some emerging issues and opportunities for future works. As a summary, Fig. 4 shows a diagram with the main emerging trends identified.

6.1. Security

The applications discussed in the reviewed literature primarily focus on database augmentation and style replication. In the domain of data-driven generation methods for handwriting, diffusion models have emerged as a promising approach (e.g., [16,22,57,78,89,96,98,125]). These models provide enhanced flexibility and improved generation

Table 9
Publicly available codes.

Ref	Web page	Short description
[14]	github.com/ankanbhunia/Handwriting-Transformers	An off-to-off transformation for copying styles. They use an encoder–decoder architecture, with "encoder (Enc), transformer decoder (Dec) and cycle loss (CL)" [14]
[111]	github.com/tlc121/FsFont	They create a system to generate handwritten-like type fonts in languages with many characters.
[70]	http://dsd.cs.brown.edu/	An on-to-on transformation for copying styles. They use the method Decoupled Style Descriptors (DSD), which makes style variations in a way that the style of the character is dependent on the writer.
[73]	github.com/LaiSongxuan/SynSig2Vec	An on-to-on transformation for augmenting databases. They use a sigma-lognormal model.
[113]	github.com/magenta/magenta-js/tree/master/sketch	An on-to-on transformation for augmenting databases. They use a sigma-lognormal model and a Variational Autoencoder.
[25]	github.com/dailenson/SDT	An on-to-on transformation for copying styles in Chinese and other strokes-based character-rich languages. They use a style-disentangled Transformer, which is a "dual-head style encoder", a "content encoder" and a "transformer decoder"[25].
[112]	github.com/ShusenTang/WriteLikeYou	An on-to-on transformation for copying styles. They use a content encoder, a style encoder, and a decoder. All are RNN architectures.
[63]	github.com/jibo27/hw_gan	An on-to-on transformation for copying styles. They use a GAN.
[64]	github.com/KAKAFEI123/Stroke-cCycleGAN	An on-to-off transformation for augmenting databases. This code is a stroke width modifier, for making the lines of the synthetic signatures more like human.
[88]	github.com/M4rt1nM4yr/spatio-temporal_handwriting_imitation	An off-to-on-to-off transformation. They subdivide the tasks and use the knowledge of algorithms.
[42]	github.com/Nikolai10/scrabble-gan	An off-to-off transformation for copying styles. They use GAN.
[99]	github.com/aimagelab/VATr?tab=readme-ov-file	An off-to-off transformation for copying style. They use a transformer encoder–decoder architecture.
[20]	github.com/IMU-MachineLearningSXD/script-level_aug_ICFHR2022	An off-to-off transformation for augmenting databases. They transform the offline to a Bezier curve.
[66]	github.com/omni-us/research-GANwriting	An off-to-off transformation for copying styles. They use GAN.
[105]	github.com/MattAlexMiracle/SmartPatch	An off-to-off transformation. They enhance a patch discriminator. It follows the previous one.
[95]	github.com/koninik/WordStylist	A text-to-HW synthesis. They use a conditional Latent Diffusion Model.
[77]	github.com/lsflyt-pku/DeepCalliFont	A text-to-HW (font) synthesis. They use image synthesis and sequence generation.
[114]	github.com/EDM-Research/VATr-pp	An off-to-off transformation for copying styles. They use a Visual Archetype Transformer, and then, they create an evaluation protocol.
[117]	morphoboid.labri.fr/ihr-nom.html	A database of old Vietnamese.
[34]	github.com/asciusb/21SyntheticStylesNom-Database/	A database of Chu Nom characters and steles.
[28]	github.com/hachiro-2001/Bengali_Compound_Characters	A database of Bangla Compound Characters
[115]	github.com/tallesbrito/continual_sigver	Both model and inverted data for conducting knowledge distillation about real offline signature characteristics to other backbones or architectures.

quality by gradually refining images through processes that capture intricate details and diverse writing styles. However, creating effective duplicates and synthetic samples using zero-shot, one-shot, and few-shot learning remains a challenging research frontier [3,29]. At the forefront of technological challenges, the use of synthetic data to train handwriting-based systems presents significant industrial hurdles. Addressing this issue could enable the design of fully synthetic end-to-end systems, eliminating the need for real data and ensuring compliance with stringent data protection regulations.

Another challenge is distinguishing whether handwriting was produced by a machine or a human. With the advancement of AI-based generative techniques, the threat of synthetic attacks necessitates the development of robust bot detectors. These act as security layers to identify synthetic handwriting through watermarking, offering critical safeguards for e-security and e-health applications.

Despite progress in recent years, there remains room for improvement in reducing errors in handwriting recognition systems. As smartphones, tablets, and other digital devices play an increasingly central role in daily tasks, protecting users' private information is paramount. Forgers continually devise new methods to breach systems, underscoring the need for constant refinement and reinforcement of system defences. This goal can be achievable in part through advancements in handwriting synthesis.

Although the current application of synthetic writing is limited to certain areas, its potential remains largely unexplored. Beyond its use in training handwriting recognizers, a wide range of future applications remain to be discovered. Automatic signature verification has drawn attention in the U.S. electoral system [2], particularly due to the allowance of mail-in voting, which requires a signature to verify the voter's identity. During the recent presidential election, in 2020, over 65 million registered voters opted to cast their ballots by mail [61]. Signature mismatches stand out as one of the primary reasons for rejected votes. Essentially, a one-to-one comparison is required for authenticating the return envelope, presenting a challenging task where online data augmentation could enhance the robustness of the automatic verification process.

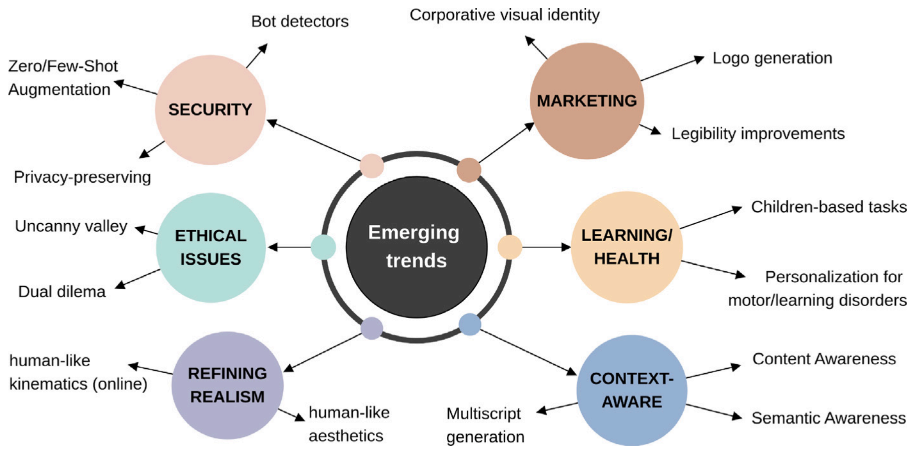


Fig. 4. Emerging trends and opportunities in handwriting synthesis.

6.2. Learning and health difficulties

An underexplored area in handwriting synthesis is its potential for early diagnosis or monitoring of diseases. Few approaches in the literature address this application. Building extensive real databases of impaired handwriting could enable meaningful statistical evaluations between real and synthetic handwriting, improving the perceived realism and trustworthiness of synthetic specimens. In this context, there are also opportunities to design longitudinal synthetic databases that capture handwriting across different stages of life: from childhood to adulthood and into the elderly years. This socially impactful research could benefit a wide range of stakeholders, including physicians, patients, and their families.

Furthermore, interactive platforms and tablets are increasingly being used for handwriting practice, particularly in children. Exercises involving personalized strokes with the style of a particular child can make the experience more engaging and enjoyable. Similarly, patients recovering from strokes or dealing with motor impairments could benefit from graphonometric-based rehabilitation exercises. These exercises, incorporating their healthy handwriting patterns, could enhance their recovery process.

6.3. Context-aware

This refers to the generation of handwriting that accounts for contextual factors, producing results that are more coherent and adapted to a particular style or content. For instance, formal letters might be synthesized with a neat, uniform appearance, whereas sticky notes could adopt a more casual, cursive style.

Synthetic handwriting can also be adapted to fit specific templates, such as forms or documents, by emphasizing elements like keywords, names, or capital letters. This semantic or spatial awareness may also consider details such as the placement of a signature within a designated box or adherence to specific page margins.

Another area requiring greater attention is the synthesis of non-Latin scripts. Current research predominantly focuses on Western scripts, followed by Chinese. However, there is a noticeable gap in studies addressing Indic scripts, Cyrillic scripts, and multilingual handwriting generation. This highlights the need for unified models capable of generating handwriting across multiscript environments.

6.4. Marketing and aesthetics

In the field of beauty marketing and advertising, synthetic handwriting could be used to personalize advertisements and tailor messages with more persuasive content. For example, handwritten logo branding for companies is a potential application. Many renowned international companies have logos with minimal text accompanied by elegant flourishes.

Similarly, synthetic handwriting models could benefit politicians, CEOs, or other VIPs who frequently sign letters intended for widespread distribution. These models could duplicate their personal signatures and generate more aesthetically pleasing variations, which may potentially reinforce certain emotions in the reader.

Improving legibility is particularly important for handwriting in contexts such as medical prescriptions, legal and official agreements, invoices, orders, or any personal text meant to be read by others. Enhancing the clarity of handwriting in these scenarios could significantly reduce errors and misinterpretations.

6.5. Improving handwriting realism

This involves replicating the natural variability, imperfections, and human-like characteristics. It is important to note that additional imperfections in handwriting may arise from the device used, which can introduce artifacts and noise into the writing.

On the one hand, human-like trajectories can be achieved by personalizing stroke variations to mimic natural fluctuations or baseline drift. Tremor, if present, is another key factor, especially in the realism of elderly handwriting.

On the other hand, kinematics and temporal properties should be considered in online handwriting. Further research into the realism of kinematic theory [40] would advance human-centred generation of velocities, accelerations, and jerks.

This kind of refinement in realism makes security issues more challenging. In fact, we can define a security-generation cycle that feeds back into itself. The result of such a cycle would be improvements in both generation and security.

6.6. Ethical issues

Finally, we cannot ignore the ethical concerns. There are risks associated with potential misuse, privacy violations, and the impact on human authenticity and creativity. Additionally, excessive perfection in handwriting generation may trigger the uncanny valley effect. Perfect duplicates of human handwriting could evoke discomfort or unease due to subtle inconsistencies in style and flow.

Other ethical risks involve the use of duplicate signatures to attack automatic verifiers. A simple trojan in a system that steals an enrolled genuine signature could have dramatic consequences, enabling impersonation without consent. Therefore, countermeasures against

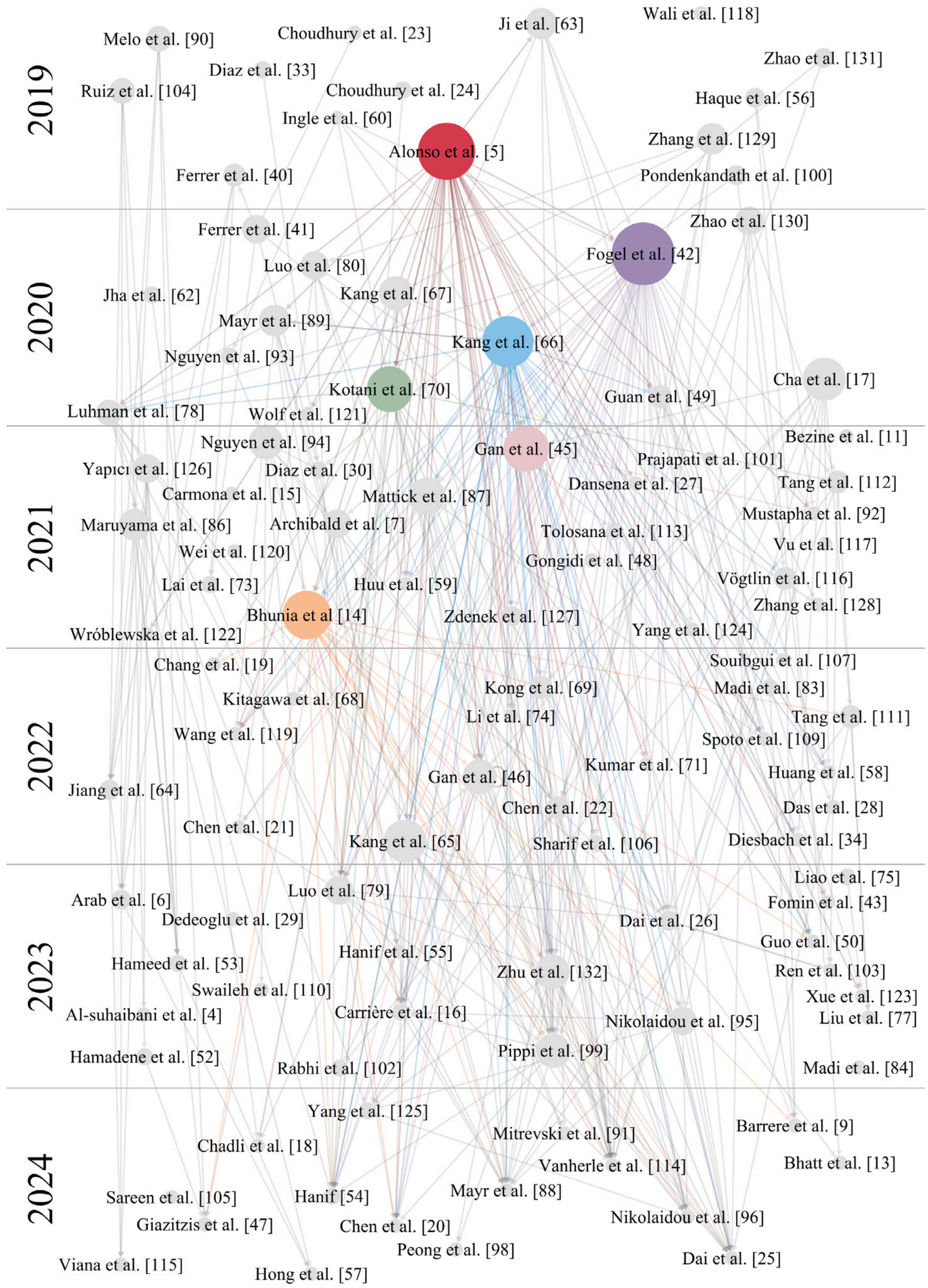


Fig. 5. Article connections: year-wise distribution and citation relationships. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

such attacks should be prepared. Other sensitive documents, such as contracts or wills, could also be threatened by synthetic attacks.

In summary, there is a dual dilemma between the benefits and harmful uses of this technology. While many opportunities have been highlighted in this article, the same technology can be exploited for malicious purposes, espionage, or even propaganda.

7. Discussion and conclusions

This review has achieved a comprehensive understanding of the literature. In Fig. 5, all contributions are arranged by publication year, in descending order. The papers on historical data and non-Latin scripts are slightly offset to the right. The size of each node in the paper represents the number of times it was cited by other articles considered in this review. Papers that received more than ten citations are highlighted in a colour other than grey.

We found that Generative Adversarial Networks (GANs), Convolutional Neural Networks (CNN), and other deep-learning schemes have been extensively studied for synthesis, seemingly surpassing traditional mathematical approaches, such as sinusoidal or sigma-lognormal models.

On-to-off transformations are scarce. This is likely because recognizers excel in performance when processing online handwriting. However, this transformation is particularly significant for fostering synergies between offline and online recognizers [44].

However, a more challenging task remains unsolved in off-to-on transformation. While many studies have achieved stroke trajectory recovery or vectorization of the traces, only a few have successfully synthesized dynamic aspects, including velocities and pen-ups. These dynamic elements play a critical role in developing synthetic databases.

Solving this highly complex transformation would represent a significant advancement for offline recognition systems. It allows for extraction of more information from the specimens. Additionally, by incorporating complementary online training data, we can create more robust authentication systems while ensuring writers' privacy.

As regards the evaluation methods, our analysis revealed that the most widely used were Fréchet Inception Distance (FID), Dynamic Time Warping (DTW), and verification or recognition systems. There are ongoing efforts to refine these metrics, to make them more adequate for handwriting synthesis.

Furthermore, investigation of handwriting synthesis would enhance transparency and reproducibility, while also making more code publicly available to the scientific community. Not only will this ensure that claims are verifiable, it will also allow other researchers to validate and improve methodologies. This is particularly useful for new researchers entering the field.

In forensic and legal environments, synthetic writing could be employed for documenting evidence, expert reports, and court transcripts. However, its acceptability in these contexts is still under debate and would require clear regulations. Additionally, the creation of new synthetic databases in various scripts, with realistic online and offline samples, is currently under development. This not only enables the development of advanced algorithms, but also opens up the possibility of organizing benchmarks and international competitions with fair evaluations. Furthermore, text generators could be used to create personalized educational material, such as summaries, exercises, or explanations. They could also assist students with writing difficulties, enhancing their potential in education and learning. Synthetic handwriting also presents opportunities in robotics, entertainment, and video games. For example, designing virtual characters in virtual reality environments that require generation of more realistic and coherent dialogues. In summary, although current applications are limited, the future of synthetic writing promises a wide variety of possibilities.

CRediT authorship contribution statement

Moises Diaz: Writing – review & editing, Investigation, Funding acquisition, Conceptualization. **Andrea Mendoza-García:** Writing – original draft, Methodology, Investigation. **Miguel A. Ferrer:** Writing – review & editing, Supervision, Formal analysis, Conceptualization. **Robert Sabourin:** Writing – review & editing, Validation, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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