RESEARCH ARTICLE

Automation and Artificial Intelligence in the Type Design Process: Insights from an Industry Survey

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Abstract: This article investigates how automation (both deterministic and artificial intelligence–based) is integrated into professional type design practice, a field with exacting standards of craft and which relies on specific and long-established working methods. Drawing on an online survey conducted in early 2025, alongside detailed follow-up interviews with select type practitioners, we map current practices and attitudes, as well as the perceived risks and opportunities in the field of automation for type design in general, and the implementation of artificial intelligence (AI) in particular. Data analysis established that deterministic, rule-based automation is near-ubiquitous in type designers' workflows, and is already used for a variety of tasks such as interpolation, glyphset expansion, and various font engineering tasks. In contrast, AI tools have currently only been adopted by a minority of practitioners, and are largely being used for adjacent tasks such as writing code, gathering project documentation, or generating proofing strings. The majority of respondents expressed strong resistance to automating what they identify as the creative core of their work (e.g., sketching, drafting a basic alphabet, marking proofs), but show willingness to delegate the most labor-intensive, technical operations to software, with kerning repeatedly identified as the leading candidate for further automation—provided that human oversight and decision making remain throughout the process. Ethical concerns (such as training data provenance, lack of transparency, and environmental costs) lead to a cautious attitude towards generative AI, a position also fueled by some expressed anxieties about corporate concentration. We argue that sustainable and worthwhile innovation in typeface design should prioritize assistive tools that are transparent and encourage human decision-making, in order to optimize routine work without compromising iterative practices through which designers acquire judgement. Such tools would ideally balance streamlined workflows with the acquisition and reinforcement of highly specific skills, which in turn enable designers to preserve qualitative typographic standards.

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Implications for practice: The integration of automation and artificial intelligence within type design should serve to augment designers' creative and critical agency. Automated processes can effectively support technical and repetitive tasks—such as spacing, proofing, and data handling—allowing practitioners to concentrate on conceptual and aesthetic decision-making. Transparency and user control are central to this relationship; systems must remain interpretable and open to designer intervention. Ethical considerations warrant continued professional attention as automation becomes pervasive. Collaboration among designers, educators, and developers will be essential to ensure that emerging tools are aligned with the discipline's values of craft, intentionality, and typographic quality. Sustained engagement with scripting and AI literacy will empower designers to critically shape automated systems within their evolving practice.

Keywords: artificial intelligence; creative practice; ethics; intellectual property; type design

1. Introduction

1.1. Context and Aim of the Research

Artificial intelligence (AI) products and assistants are being inserted into every creative field, from writing text to programming to generating images and video. While there are currently many reservations about such systems, a broad spectrum of users have grown accustomed to these new tools. Until now, typeface design seems to be one of the few creative disciplines not yet penetrated by AI, for a few unique reasons.

Typeface design requires a particular workflow and has specific quality criteria that make it challenging for AI and machine-learning processes to achieve a sufficient standard. Letterforms must adhere to strict typographic conventions and optical adjustments to ensure readability and aesthetic harmony at minute details (Unger, 2018, p. 63), so one of the primary challenges in using generative AI for type design is achieving this high level of precision. Generating accurate and coherent typographic systems involves complex issues such as shape consistency across whole character sets, as well as spacing, kerning (which also requires building kerning groups), developing OpenType features, hinting, i.e., many crucial steps that are difficult for AI to master without developing extensive and nuanced training data.*

* Questions of "training" and the creation of "training data" will arise several times in this article. There are no standardized methods for creating training data from font files or type designs, nor for training algorithms with such data. Different decisions can be made at every stage, from the types of data included, perhaps only shapes, or also font metadata, to the sources from which the data is drawn and the way it is prepared. Possible sources include scanned typeface specimens, rasterized images, and vector outline data in a range of forms and formats. Such variation only adds to the opacity of the process and would logically lead to different outcomes.

For the Latin alphabet specifically, typeface design is an industry that is concerned with creating original work in increasingly minute variations of the same basic themes established over the last 500 years. It operates within the contradiction that a new typeface must look unique and distinctive, yet simultaneously so in line with history that "only very few recognize its novelty," as said by Stanley Morison (1930/1951, p. 7). Little wonder then that the industry's culture is full of possessiveness, where type designers and foundries are watchful of both being plagiarized as well as plagiarizing others (Heller, 2015; Monotype, 2025).

There are also far fewer people who make typefaces—or even make conscious choices about typefaces in a professional way—than there are people generating images, writing computer code or school essays using AI tools. With training costs reportedly in the billions of dollars for the top-ranking models such as Anthropic's Claude or OpenAI's ChatGPT (Buchholz, 2024; Henshall, 2024), the economic viability of a font-generating large language model (LLM) is questionable. This concern sets aside a further unresolved issue in current AI experiments in type design, namely whether a sufficiently large body of typefaces exists to provide adequate and viable training data.

Given the rapid advances in AI and the specific challenges posed by typeface design, it seems to be an appropriate time to reflect on the current and future impact of AI on the type design industry. A team of designers and educators from the Master Type Design at École cantonale d'art de Lausanne (ECAL / HES-SO)* came together to investigate the specificities of type design as a creative industry, and to better grasp the challenges and potentialities that AI brings to the community.

We set out to explore the following questions: How are current advancements in AI already affecting the type design industry? What are the perceived risks and opportunities according to type designers, font engineers and foundry owners? And how can we develop a collaborative model between designers and computer scientists that ensures ethical and qualitative use of AI in type design?

1.2. Automation and Typeface Design: A Shared Legacy

> The desire to reduce human intervention in the production process is the primary driving force that led to typography's departure from handwriting. Type designers, or designers at large, have always been practitioners of automated craft. (Wang, 2024, p. 7)

* The "Type Tomorrow" research project ran from January to June 2025 and was funded by HES-SO as part of its "Appel à projets stratégiques 2024: l'intelligence artificielle au service de la société: opportunités, défis et risques." The research was led by Alice Savoie, Kai Bernau, Raphaela Haefliger and Wayne Daly (ECAL / HES-SO), with support from Sebastian Baez-Lugo (EPFL+ECAL Lab).

Use of computation to systematize or automate letterform generation predates AI by several decades. A pivotal early example is Donald Knuth's Metafont (1979), a parametric system that allowed users to define letterforms through mathematical descriptions of letter parts and their relationships (Knuth, 1979, 1985; Figure 1). Although revolutionary, Metafont was limited in visual quality and adoption, partly due to its steep learning curve and the difficulty of capturing typographic nuance in code.

The availability of digital tools opened up new perspectives for a young generation of designers (Poynor, 2003, p. 96), especially when they became readily available on consumer computers. In the late 1980s digital font editors such as Fontastic and Fontographer, in combination with the Macintosh computers they ran on, became essential tools for type designers, allowing for precise control over typefaces. These programs automated only very few parts of the process, such as certain aspects of shape drawing and storage of those drawings in the correct locations inside a font file. In the early 1990s, Petr van Blokland (with Just van Rossum and Erik van Blokland) produced a "hacked" version of Fontographer called RoboFog (Ulrich, 2022, p. 325). It included an application programming interface (API) in the then-new Python programming language, which allowed an extension of the software to automate far more tasks through scripting, laying important groundwork for the culture and the perceived tasks of the profession.

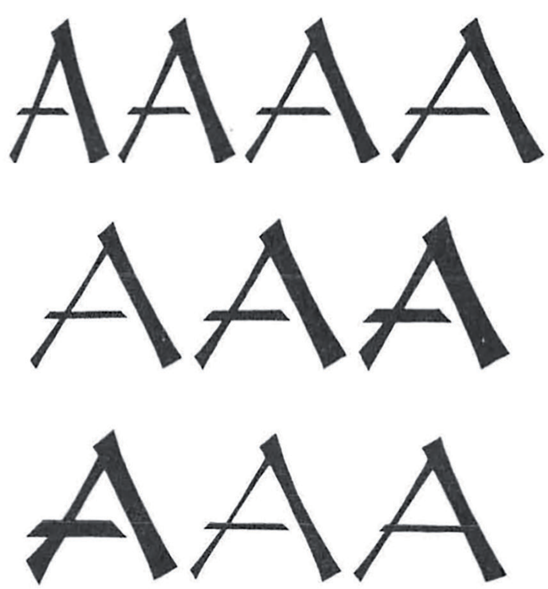

Figure 1. Variations on capital letter **A** using different parameters from Metafont. Originally published in Knuth (1985), p. 52.

Towards the end of the 1990s, the dominant font editor was Fontlab, which came with a Python interpreter already built-in, on top of which Erik van Blokland, Just van Rossum and Tal Leming built RoboFab, "a pythonic API to FontLab's native objects" (FontParts, n.d.), heavily based on RoboFog (RoboFont, n.d.-a). A lively scene of individual type designers with a "DIY automation ethos" sprang to life from the possibilities provided by RoboFab, from small helper scripts to whole applications like MetricsMachine for kerning, or Superpolator for interpolation.

While interpolation between letter shapes as part of the type design process has been practiced since the 1970s, beginning at the firm URW with its Ikarus software (Ulrich, 2022, p. 275), the role of computation in type design expanded only in the late 1990s with technologies such as Adobe's Multiple Master and Apple's TrueTypeGX formats. These formats first allowed typeface *users,* not just typeface *designers,* to interpolate between extremes. Apple's GX Variations formed the basis of the OpenType variable font format published in 2016. These systems still required human authorship of the base designs (Figure 2).

In the 2010s, new font editors such as Glyphs and RoboFont emerged, thanks to the dedication of a handful of type designers and computer programmers eager to develop contemporary tools. These two programs are diametrically opposed with regards to their view of integrating automation: Glyphs integrates many powerful functions and ways of optimizing and automating standard workflows ("Whose workflows?" goes one common critique of this approach) that offer much guidance and simplicity. RoboFont is a continuation of the lineage that began with RoboFog and RoboFab and abstains from bringing its own decisions to the user, instead requiring the user to think about and choose or create their own automations (RoboFont, n.d.-a). Famously, not even a tool to draw rectangles and ellipses is included with the core RoboFont application. Both font editors encourage, but RoboFont *requires* designers to add programming to their skill sets.

Communities that discuss and share plug-ins/extensions and scripts exist for both platforms as witnessed by public directories and dedicated extension managers (Robofont Mechanic and Glyphs Plugin Manager, respectively), and they are testimony to designers' changing practices.

Contemporary type designers thus have at hand powerful tools that are seamlessly integrated into their design workflow. Many are embracing the use of programming and automation as part of their practice. Some designers with solid programming skills are marketing tools that can be easily integrated into a design process, such as Tim Ahrens' Font Remix Tools (Remix Tools, n.d.) and Kern On (Kern On, n.d.) or Tal Leming's MetricsMachine (Metrics Machine, n.d.).

Figure 2. Multiple Master axes implemented in the Myriad typeface family, designed by Robert Slimbach and Carol Twombly for Adobe Systems in 1992, and Minion, originally designed by Robert Slimbach for Adobe Systems in 1990. Originally published in Adobe Systems Inc. (1992, p. 7). Image: courtesy Musée de l'imprimerie et de la communication graphique Lyon.

1.3. AI, the Next Step in Type Design Workflow Automation?

The authors note that the term AI is often used rather loosely by themselves, the survey participants, the cited sources, and the broader audience. In this context, it may refer to systems that range from expert-operated specialized software trained on narrowly defined input data to produce narrowly defined outputs, to general large language models trained on vast internet-scale datasets that generate statistically probable responses to a wide range of queries. As many such systems are proprietary, it is not always possible to determine where a particular AI system lies along this spectrum.

A number of studies, articles and projects have explored the potential of AI for typography and typeface design, including experiments by computer scientists (Gao et al., 2008; Bataineh et al., 2012; Mohammed Javed et al., 2014; Murdock et al., 2015; Wang et al., 2015; Diem et al., 2017; Shinahara et al., 2019; Srivatsan et al., 2019; Wasim et al., 2024). Many of these experiments tackle isolated typographical aspects such as baseline detection (Murdock et al., 2015) or serif recognition (Wasim et al., 2024). Others attempt to generate entire alphabets based on fragmentary data—a practice that, if successful, opens up dizzying prospects for typeface generation. In 2018, Azadi and colleagues applied generative adversarial networks (GANs) to generate images of alphabets, presenting a model called "Multi-Content GAN" that can synthesize missing characters by learning from a few examples (Azadi et al., 2018). While their study demonstrated that GANs could produce stylistically coherent alphabets, a number of issues remained unsolved: the set of letters generated only included capital letters, featuring highly decorative styles unsuitable for continuous reading. Furthermore, the experiment was based on images rather than vector-based fonts. This is also the case for the Google Labs GenType experiment (Google Labs, n.d.; Figure 3), which generates illustrative alphabets through a user prompt.

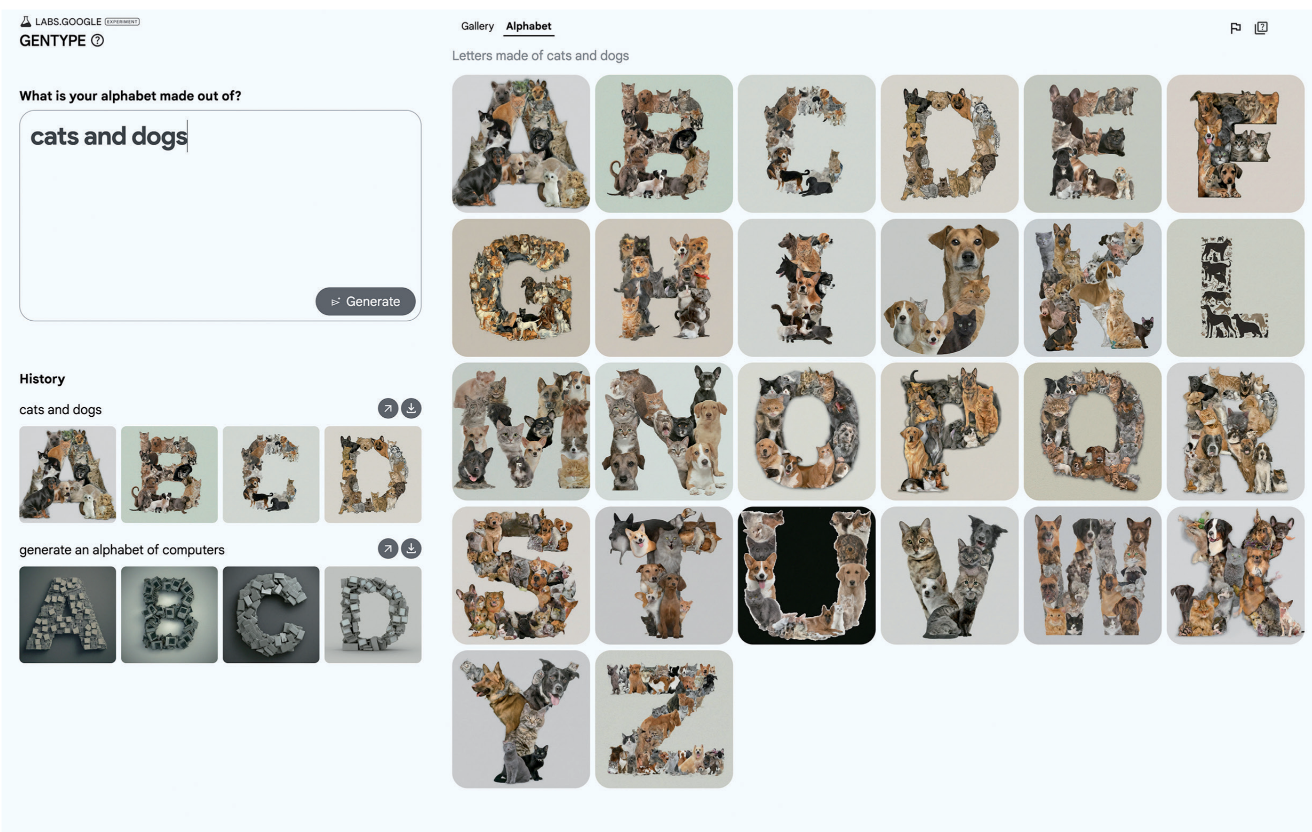

Figure 3. An alphabet made of cats and dogs, AI generated using the GenType model by Google Labs, October 2025. GenType is a trademark of Google LLC. Screenshot by the authors.

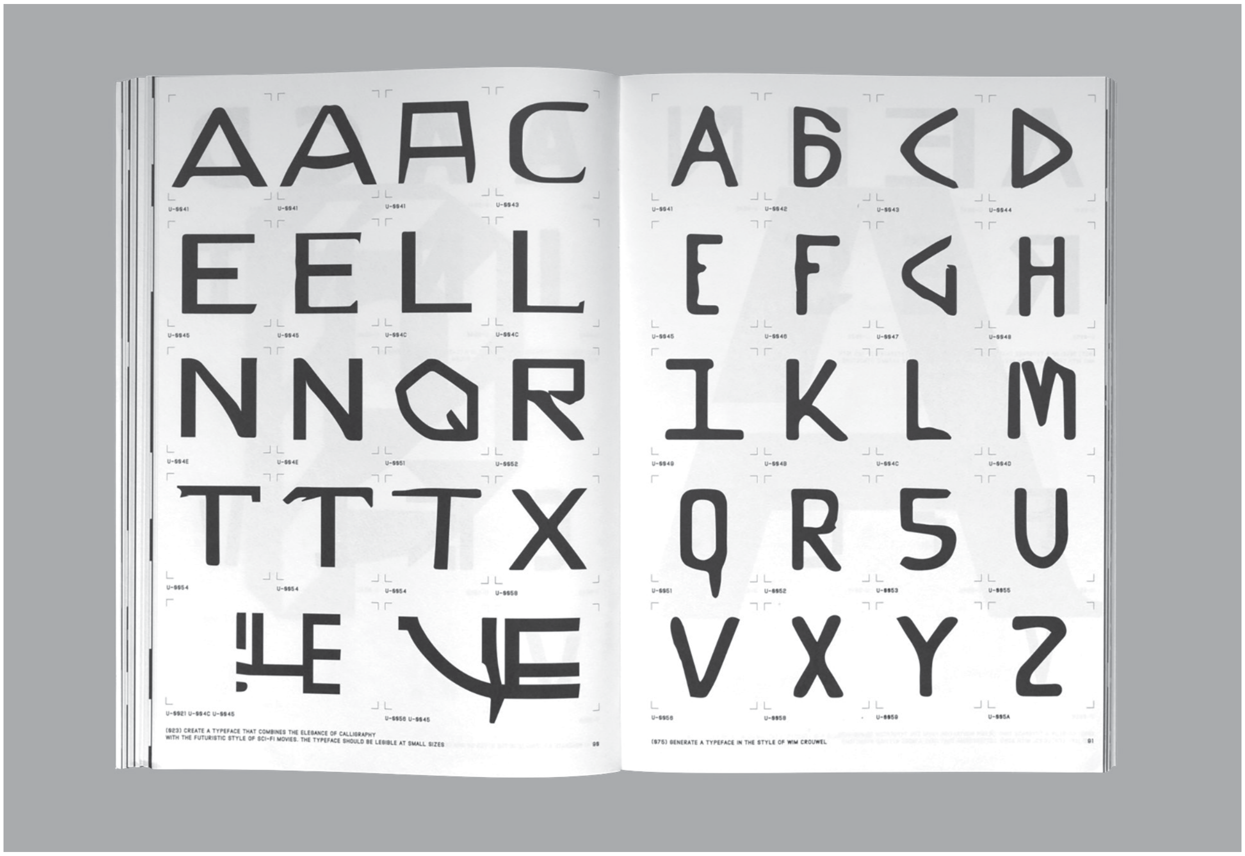

Figure 4. Letterforms generated with AI by Orlando Brunner. Published in Brunner (2024).

The last few years have seen initiatives which use generative AI and machine learning to output actual typefaces in vector format. Carlier et al. (2021) opened the way by generating and manipulating scalable vector graphics (SVGs) using deep learning techniques. Unlike raster images, vector graphics are defined by mathematical formulas, allowing them to scale without loss of quality. The team's research opened up new perspectives for generating character shapes, and potentially full typefaces. Initiatives to produce OpenType typefaces also recently emerged from independent type designers, programmers and type foundries (Brunner 2024; NaN Foundry, n.d.; Wentzel 2024; Figure 4). While these experiments are worthy of consideration, the resulting typefaces remain rudimentary in their design, often encompassing only capital letters, and displaying obvious flaws. The recently beta-launched Typograph service promises to "generate a typeface in seconds" from verbal prompts (Typograph, n.d.). However, co-founder Viktor Persson explains that the typefaces are actually created by more conventional means, with a chat-AI based interface sitting between the user input, and a variety of typeface models that are blended and interpolated conventionally, through the interpretation of the chat prompts.* In recent years, programmers and typeface designers have joined forces and experimented with AI-assisted kerning.†

Most of these initiatives have raised fierce debates within the industry regarding the dataset used for training the algorithms, and type foundries have started updating their licenses to protect their designs from being exploited (Lineto, 2024). In theory such license addenda would on the one hand protect designers' creations from being incorporated into learning data and closely imitated by a theoretical AI font creation software; on the other hand, it would limit the quality of the output dramatically. In line with the wider AI industry, companies might just train their models on copyrighted and/or pirated data anyway, and claim that "it would be impossible to train today's leading AI models without using copyrighted materials," as OpenAI responded to an inquiry of the U.K. House of Lords' Communications and Digital Select Committee in relation to a copyright lawsuit brought against OpenAI by the *New York Times* (LLM0113, 2023).

It remains unclear whether relying only on Open Source typefaces can create quality results. Training outcomes depend not only on the amount of available data, but also on the quality and consistency of that data, as well as on the methods used to translate training material (such as outline descriptions or pixel images) into generated outline structures. These processes involve numerous technical choices that can strongly influence the quality of the output. Nonetheless, access to large and carefully curated typeface collections may still confer an advantage, which would mean that type foundries with the largest intellectual property (IP) resources are best positioned to assemble high-quality training datasets.

Beyond its own legacy library, Monotype Inc. has been buying type foundries and catalogs at a quick pace over the last 20 years,‡ and now claims to own over 150,000 fonts, completely dominating the market in many aspects including its ability to create AI training sets with this font data. At the moment, Monotype's efforts in the field of AI seem to be more in the field of categorization and recommendations of existing

* Viktor Persson interviewed by Kai Bernau, June 23, 2025.

† Some of these experiments were discussed in interviews carried out as part of this research project: see Cem Eskinazi interviewed by Raphaela Haefliger, June 26, 2025; Tal Leming interviewed by Kai Bernau, May 30, 2025.

‡ Notable acquisitions include: Linotype (which itself had previously absorbed font libraries from the likes of Deberny & Peignot, Haas and Stempel), 2006; China Type Limited, 2006; Ascender Corp., 2010; Bitstream and MyFonts, 2012; FontShop and the FontFont Library, 2014; URW Type Foundry, 2020; FontSmith, 2020; Hoefler & Co., 2021; Berthold type foundry, 2022; Milieu Grotesque foundry, 2023; Fontworks, 2023; 39 typeface families by David Berlow from the Font Bureau Library, 2023; Colophon Foundry, 2023; the rights to the catalog of SharpType, 2024; DSType font collection, 2024 (Monotype, n.d.-d; Luk, 2023; Fonts In Use, n.d.).

fonts (Monotype, n.d.-a) as well as assistants—a "creative partner, working alongside [designers] to add to [their] human creative capacities"—but also adds "Expect more and expect it soon" (Monotype, 2025). In 2025, Monotype announced a partnership with Blaze Type to conduct experiments in AI-automated completion of character sets (Monotype, n.d.-b), with improved formal results, in vector format. On the page describing the experiment, no mention is made as to the training data, but in an interview, Monotype's Emilios Theofanous describes "a tool for typographic AI generation" where users provide "input of specific characters and […] get back either an expanded character set […] or alternates." He notes that at the moment the tool is "only used internally," "only for exploration and experimentation" and that for training data it uses "just Monotype's IP," not that from Monotype's partners.*

2. Methodology

2.1. Aim and Context of the Survey

In response to this context, our team decided to run a survey to better understand how professionals—type designers, font developers, font engineers, etc.—perceive the evolving role of AI in type design. We also wanted to identify what parts of their process designers are willing to delegate to a machine, and which parts are considered as meaningful, enjoyable, or highly dependent on human intervention. The survey further shed light on the perceived risks and opportunities associated with AI in type design. We felt that understanding these perceptions was crucial for addressing concerns and identifying areas where AI can be most beneficial, or potentially harmful.

The survey was conducted through the online platform Survey King and was publicly accessible for six weeks. Respondents' participation was entirely voluntary and responses remained anonymous, analyzed in aggregate form only.† The study was carried out in accordance with our institution's research procedures and ethical guidelines, with internal approval secured before data collection commenced. To maximize ease of use for participants, all individual questions were optional, resulting in variable sample sizes for each analysis. When quoting open responses from the questionnaire in the

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* Emilios Theofanous interviewed by Alice Savoie, July 7, 2025.

† The survey was conducted between February 18 and March 31, 2025 and was promoted through social media (posts on Instagram and Mastodon, through ECAL-affiliated accounts as well as personal accounts of team members, friends, and colleagues who kindly shared or republished the survey), a conference (an announcement during the Automatic Type Design 3 conference in Nancy) and email (via the ECAL newsletter system, targeting industry members, ECAL alumni, and others). Respondents had the option to provide their email address in the final stage of the survey, as a means to be kept informed about the publication of survey results. Recipients were also encouraged to share the survey with their own contacts.

sections that follow, we reproduce them verbatim and attribute an anonymized identifier to each respondent (e.g. [P35]). From a total sample of *N*=157 participants, *n*=123 completed the questionnaire, and *n*=34 submitted only partial responses.* Because no comprehensive demographic study of the type industry currently exists, it is not possible to establish how closely our sample reflects (or diverges from) the broader professional population.

Once the survey data had been analyzed, our team conducted a series of interviews to clarify and expand on some of the findings. Practitioners who collectively spanned a range of roles, geographic regions and levels of experience were invited to take part, selected purposely to discuss specific experiments referenced by survey respondents and/or to draw on their knowledge of ongoing automation and AI initiatives within their workplaces. Semi-structured interviews were either carried out through online meetings (video conference) or via e-mail. We asked interviewees to share their own views and recent experiences with automation and the use of AI in the type design process, and, where relevant, to reflect on their own or their employer's experiments. Interviewees include: Matthew Carter (founder, Carter & Cone), Cem Eskinazi (type designer, independent), Tal Leming (type designer and coder, Type Supply), Viktor Persson (founder, Typograph), Keitaro Sakamoto (type director, Morisawa), Emilios Theofanous (type director, Monotype). All conversations were transcribed, and illustrative quotations are woven into the subsequent discussion; interview quotations are not anonymized and are reproduced with the interviewees' informed consent.

2.2. Survey Structure and Analysis

Our survey was comprised of four sections:

1. Introductory and ethical information: respondents first encountered a brief statement outlining the study's aims, the intended use of the data, and the measures taken to ensure anonymity. They were then asked to confirm their informed consent before proceeding.
2. Current practice and expectations: participants detailed how they currently employ automation in their workflows, distinguishing between deterministic (i.e., rule-based) and non-deterministic (i.e., AI-driven) methods. A five-point Likert scale followed, gauging the extent to which they believe AI will reshape the type industry in the near future.
3. Propensity to automate specific tasks: using a five-point Likert scale, respondents indicated the likelihood that they would delegate each of 16 typical tasks involved in a type design process, from early sketching through final quality assurance, to

* For these 34 partial submissions, only their answers to the open-ended questions were considered, using them for qualitative sentiment analysis.

(a) deterministic scripts and (b) AI-powered tools. Open questions invited them to elaborate on which tasks they find especially tedious or enjoyable, and why they would—or would not—automate them.

4. Demographic and professional profile: the final section gathered background information: age, gender, country of residence, profession(s) and employment situation, years of industry experience, and the writing systems in which respondents routinely work. An optional comment box invited participants to add any further observations before submitting the questionnaire.

Survey analysis. The quantitative data from this online survey was analyzed using R (version 4.4.2) within the RStudio environment. Data wrangling and descriptive statistics were performed using packages from the *tidyverse* suite, primarily *dplyr* for data manipulation and *ggplot2* for visualization. Where appropriate, inferential statistical analyses were also conducted, including non-parametric pairwise comparisons, correlations, and linear regression. Qualitative data from the open-ended survey questions and follow-up interviews was analyzed using a thematic analysis approach. This process was facilitated by a rainbow spreadsheet to organize codes and identify emergent themes.

2.3. Profile of Respondents

Age and industry experience. 77% of participants fall within the 25 to 44 age bracket, with only one respondent aged over 65 and two under 24 (Figures 5 and 6). This skew almost certainly reflects the cohort most active in contemporary type design, enhancing the survey's relevance to current workflows. Even so, the relative absence of older practitioners should be taken into account when interpreting the results.

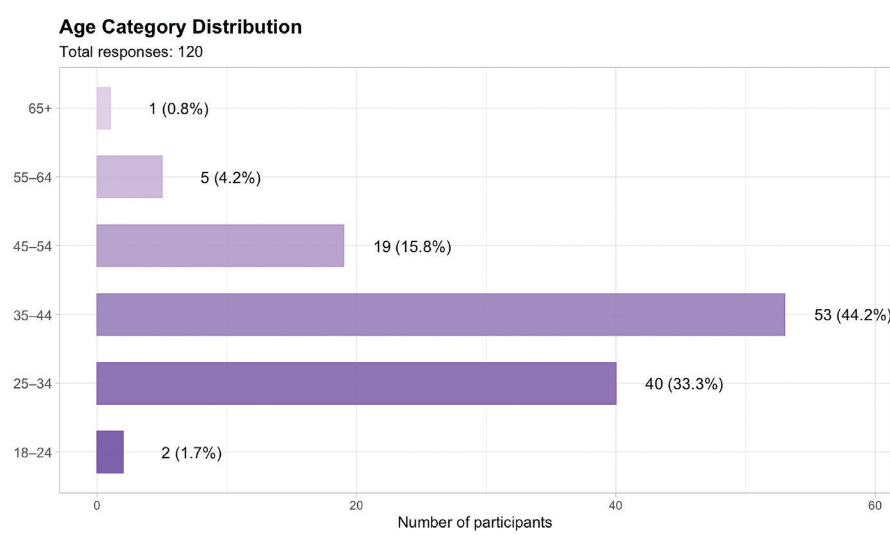

Figure 5. Survey participants profile: age category distribution (*n*=120).

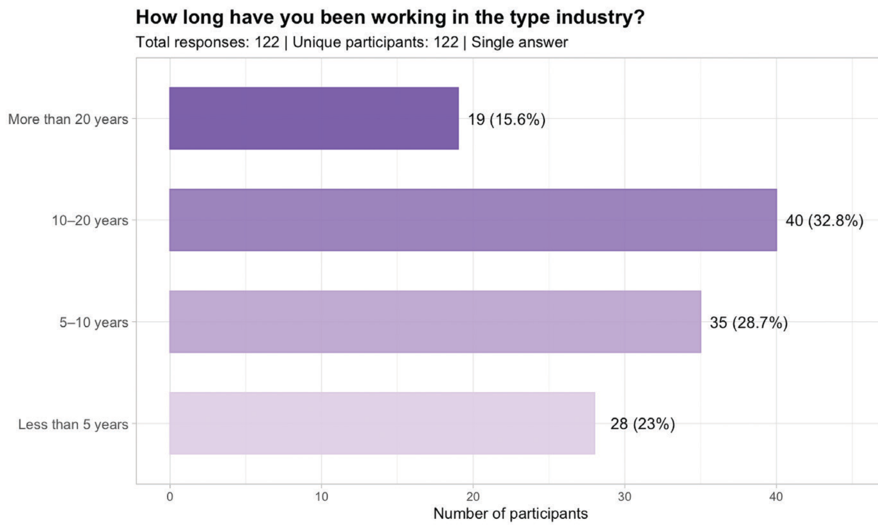

Figure 6. Survey participants profile: industry experience (*n*=122).

Professional experience is more evenly distributed. Just under a quarter of respondents (23%) have worked in the field for fewer than five years; 28.7% for five to ten years; 32.8% for ten to 20 years; and 15.6% for more than two decades.

Gender distribution. There is a clear gender imbalance in respondents' profiles, as male respondents (61.5%) outnumber female respondents (29.5%) by approximately 2:1, with a small proportion of non-binary or undisclosed respondents (Figure 7). It is likely that these figures reflect long-observed industry imbalances.

Geographic distribution and scripts. A substantial majority of participants (nearly 80%) were based in either Europe or the United States, with a high concentration of respondents living in Switzerland and France (Figures 8 and 9). Although these figures cannot be taken as representative of the global type design community, this distribution reflects the research team's institutional location and outreach channels.

Furthermore, nearly every participant reported designing for the Latin script (99.2%). Substantial minorities also worked with Cyrillic (36.4%), Greek (26.4%) and Arabic (11.6%), with smaller shares for Hebrew (5.8%). Additional scripts including Thai, Tamil (each 5%), Tai Viet and Chinese (each 4.1%) were represented by a handful of specialists. These figures highlight the heavy representation of industry professionals working in the West and on the Latin script, something that should be considered when interpreting the results, as findings may therefore not extrapolate easily to under-sampled regions.

Professional activities of respondents. 79% of respondents identified as typeface designers, but with multiple answers allowed, a substantial minority also claimed

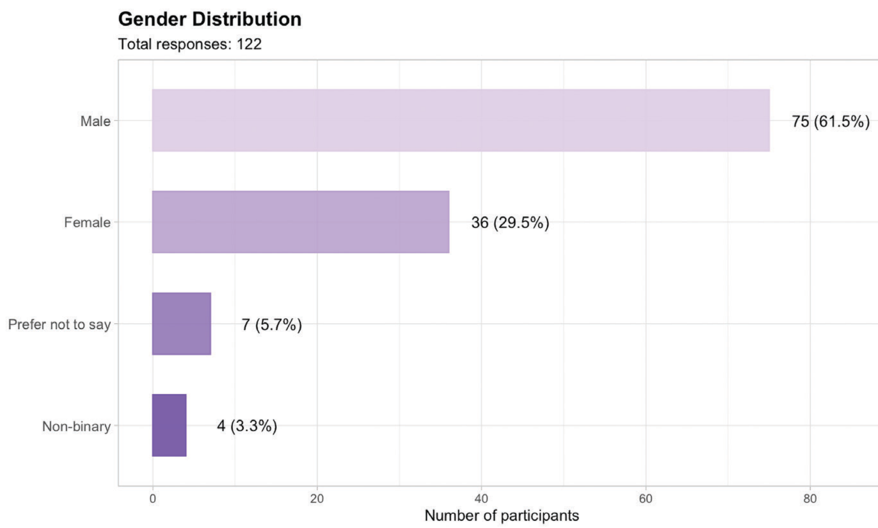

Figure 7. Survey participants profile: gender distribution (*n*=122).

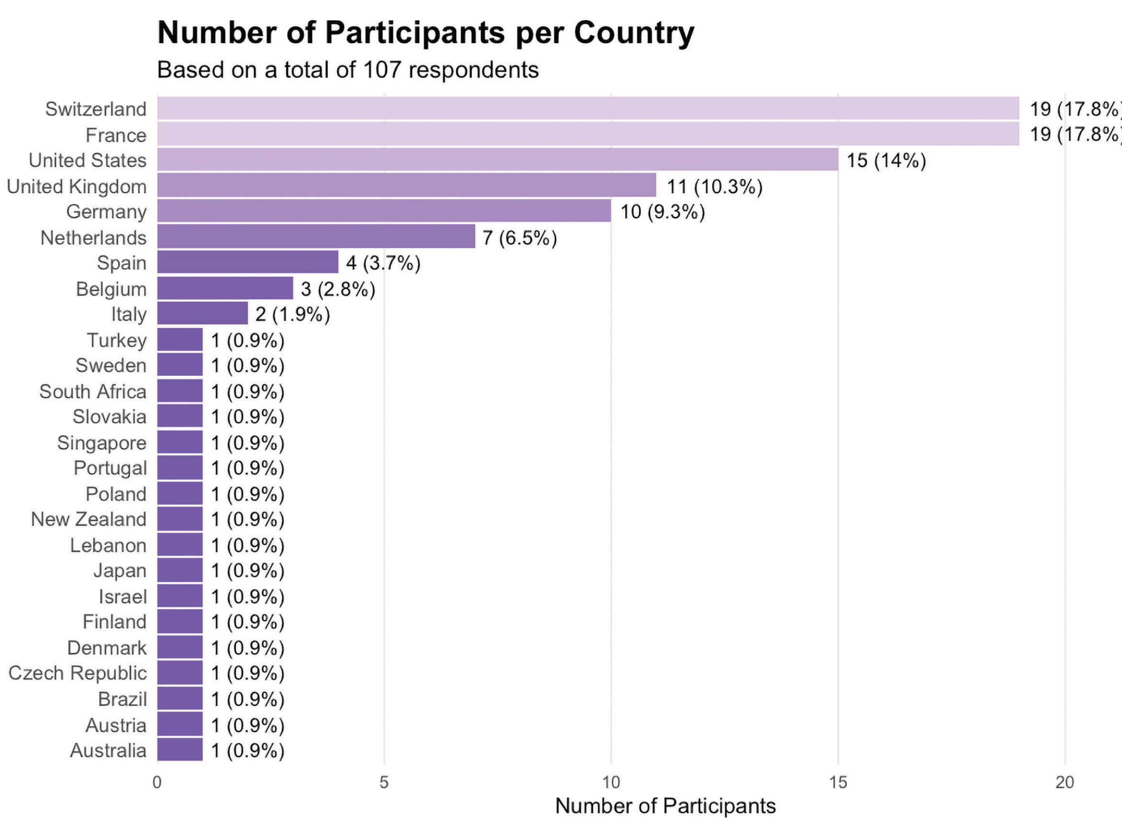

Figure 8. Survey participants profile: country distribution (*n*=107).

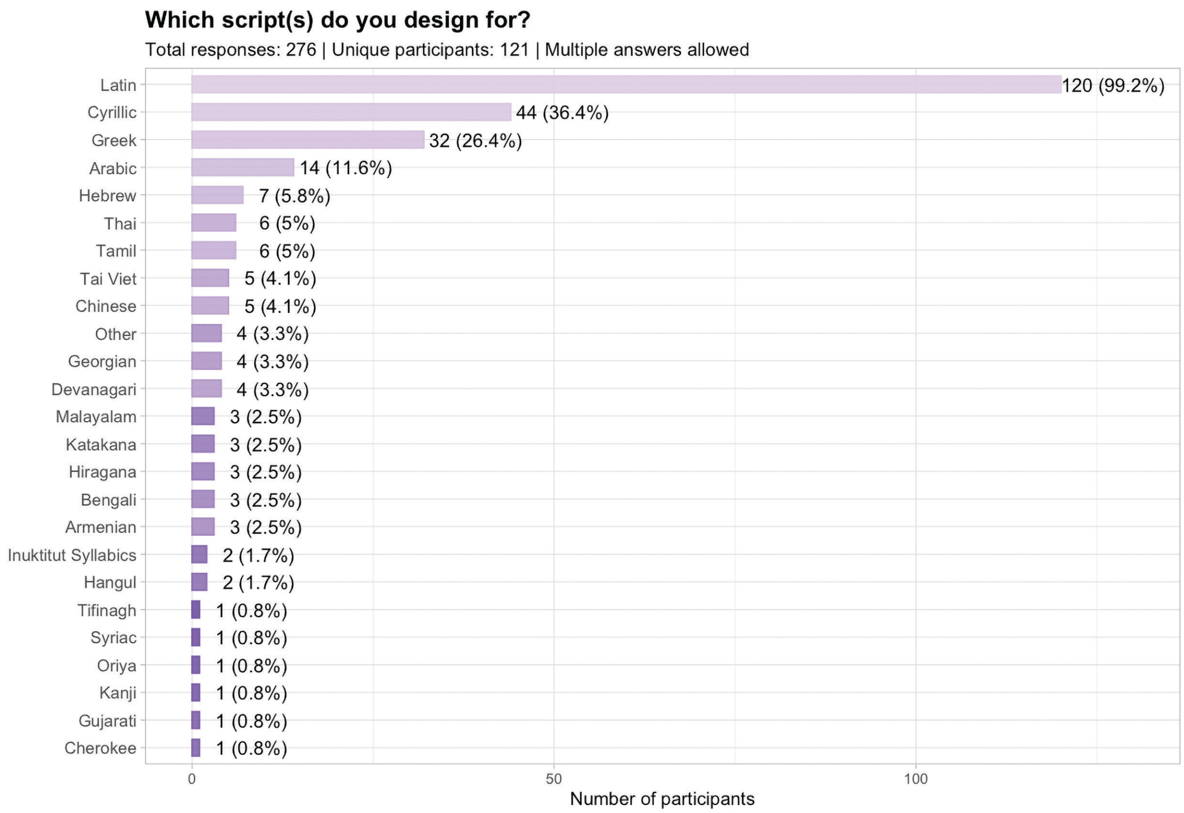

Figure 9. Survey participants profile: script distribution (multiple answers allowed, *n*=121).

technical titles such as "font developer" (34.7%) and "font engineer" (25.8%; Figures 10 and 11). Respondents also include 37.1% who identify as "Graphic designers who make fonts." Another set of responses shows that 52% identify as freelancers and 37.4% as business owners, with only 12.2% of participants claiming to work for a medium or large company of 20 people or more. These figures underscore the fact that the community includes a large number of small studios and independent practitioners. It also highlights the fact that respondents' jobs might include a diverse range of skills, and that creative and engineering roles frequently overlap.

3. Survey Findings

3.1. Current Use of Deterministic Automation in Typeface Design

Survey responses confirm that deterministic (rule-based or non-AI) automation has become an integral component of everyday practice. Three quarters of respondents (76.4%) reported employing deterministic tools in their workflow, most commonly via Python scripts or plug-ins for font editors such as Glyphs and RoboFont. Usage rates appear consistent (79–87%) across every age bracket. Whereas a higher percen-

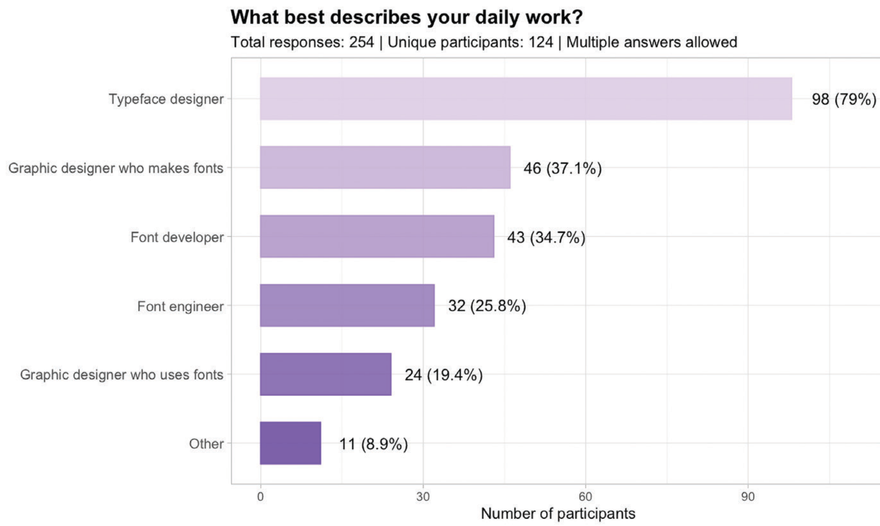

Figure 10. Survey participants profile: professional activities (multiple answers allowed, *n*=124).

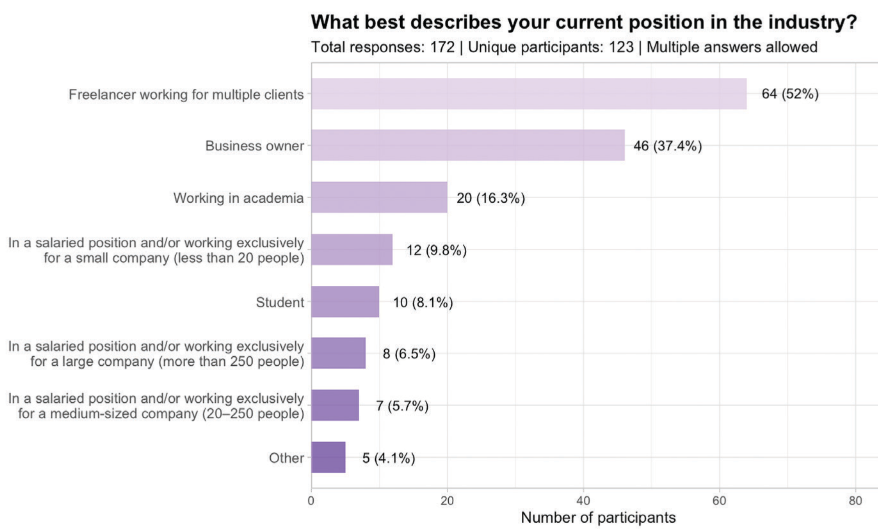

Figure 11. Survey participants profile: position in industry (multiple answers allowed, *n*=123).

tage of male participants (89%) reported using non-AI automation compared to female participants (69%), professional identity (designer, developer, engineer, etc.) does not predict willingness to automate. As a complement to these figures, pairwise comparisons (Mann-Whitney U tests) revealed no statistically significant difference in automation likelihood between genders for either the AI condition or the non-AI condition. Predictive relationships between professional roles and willingness to automate were assessed with regression analyses. Perspectives on automation benefits and drawbacks are commonly experienced by all individuals, and are not influenced by their gender identity.

A minority of respondents (approximately one quarter) reported minimal or no use of automation, citing a preference for "hand-drawn" letterforms, skepticism about tool accuracy, or a desire to understand every step of production. Respondents' comments suggest that, for many, the boundary between "manual" and "automated" work is now blurred as it could be argued that by default, anyone using a font editor and dealing with digital type relies on some kind of automation, one way or another. Deterministic automation has become foundational to digital type design, even if barely visible to some. Or as one participant asked, "Does anyone do type design without these kinds of tools?" (P134).

Deterministic automation is enlisted across a broad spectrum of tasks, including:

- Outline cleanup and error detection: scripts and applications for detecting drawing inconsistencies and issues in point placement
- Glyph scaling, glyphset expansion: designing small caps, superiors, inferiors and other derivative forms
- Interpolation and design space exploration: generating intermediate styles, supplementary weights and widths, optical sizes, etc.
- Spacing and kerning: comparing tables across masters, building kerning classes, suggesting pair values
- OpenType feature code writing
- Quality assurance: proofing, testing of exported fonts, etc.

In relation to these tasks, the survey identifies a number of utilities that have become de facto industry standards, as shown in Table 1.

Table 1. Table listing the applications and plug-ins that survey respondents reported using for specific tasks in the type design process.

Purpose	Tools and mentions by respondents
Outline clean-up and error detection	Speedpunk (3); Red Arrows (3); GlyphNanny (2)
Glyph scaling, glyphset expansion	RMX suite of tools (62); UFO Stretch (4)
Interpolation and design space explorations	Prepolator (21); Variable Font Preview (2)
Spacing and kerning	Kern On (30); Metrics Machine (5); HT LetterSpacer (4); iKern (2); LS Cadencer (1); DTL Foundry-Master (1)
Proofing and specimen generation	DrawBot (4); Word-O-Mat (1)
QA, mastering, writing OpenType features	FontTools (3); Diffenator 2 (2); FontBakery (2); Glyphs (1)

Respondents praised the RMX suite of tools in particular as a "quick sketching" environment for testing weights and widths, defining design space boundaries and producing scaled variants of base glyphs (such as superiors and inferiors or small caps) that are subsequently refined by hand. Likewise, Kern On is widely adopted to establish a first kerning pass, although many practitioners emphasized the need for manual oversight: "I always kern the basics manually and respect those values while the auto-kerning handles the rest" (P101). Prepolator is also frequently mentioned as an effective tool for cleaning up master styles prior to interpolation.

A further theme to emerge from the survey, and one that appears distinctive to the type sector, is that the majority of the software and apps mentioned by respondents have been conceived and coded by practitioners themselves. The principal font editors (Glyphs and RoboFont) as well as widely-adopted tools such as RMX Tools, Kern On, Metrics Machine and Prepolator, were all conceived, coded and released by practicing typeface designers with a fluency in software development. This dual identity collapses the conventional separation at play in most allied industries, nurturing a collegial culture in which design problems are addressed by writing and sharing code.

While deterministic automation is welcome for "boring and repetitive tasks," many respondents are keen to retain creative control. Several interviewees stressed that automation should remain subservient to judgement: "While these automation tools are helpful for providing a rough visualization, I ultimately rely on manual correction to ensure accuracy and alignment with my standards" (P38). Others drew attention to the pragmatic benefits of scripting: "A simple rule was once explained by Petr van Blokland*: 'if you have to do the same action more than ten times, then script it.'" (P224). Custom scripts enable type designers to tailor workflows to specific projects, further establishing automation as a craft resource: "I automate repetitive tasks as much as I can. I also use it to avoid human-made errors. Batch editing a large number of files or operating in a big design space can sometimes be challenging. I use custom tools to solve those problems" (P251).

3.2. Current Use of AI in the Type Design Industry

In contrast with the near-ubiquitous presence of deterministic scripting, AI tools remain a minority pursuit among professional type designers, irrespective of age. When asked "Do you currently use AI-powered tools in your type design work?," just under one third of respondents (31%) replied in the affirmative, and barely one in five (19%) reported having witnessed a "convincing" deployment of AI for type design tasks.

* Petr van Blokland is a Dutch graphic and type designer and software developer. He teaches in the Master Type and Media at the Royal Academy of Arts in The Hague.

Where AI is employed, it tends to support activities that are adjacent, but not central, to the drawing and engineering of typefaces, such as:

- Documentation and preliminary research
- Copywriting and translation assistance
- Writing or debugging code (e.g. Python scripts)
- Generating proofing documents, text samples and letter strings
- Studio administration and client communication
- Image generation and image processing

This pattern suggests a complementary, rather than competitive, relationship between AI and deterministic automation. Leading the way, OpenAI's ChatGPT dominates current usage (26 mentions), followed by LLM alternatives such as Claude.ai and DeepSeek. For code writing and debugging, respondents mentioned GitHub Copilot and Cursor, whereas tasks involving image generation prompted references to DALL·E, Hugging Face and Adobe Photoshop's generative-AI features. Overall, the data portrays AI as an emergent "studio assistant" that is valuable for ancillary work, but not yet embedded in a core type design workflow.

Of course this relationship is almost certainly shaped by current tool availability, since no commercially accessible AI applications address the critical stages of designing, developing or engineering typefaces. The handful of AI tools cited by respondents were at an exploratory stage, with mentions of initiatives specific to the development of Chinese, Japanese, and Korean (CJK) typefaces, experiments with AI-powered kerning tools, and the use of LLMs for generating typefaces. In the absence of market-ready specialist applications, machine-learning solutions remain confined to peripheral tasks, leaving deterministic automation unchallenged at the core of professional practice.

The prevailing sentiment across all participants' age groups (under 35, 35–45, and over 45) is that AI will likely transform the type design industry. When combining the "very likely" and "extremely likely" responses, a strong belief in transformation is evident (33%, 49% and 44%, respectively). Conversely, the proportion of those who felt a transformation was unlikely was consistently low (14%, 14%, and 12%, respectively). Despite these variations, a Kruskal-Wallis test showed no statistically significant difference in sentiment across the three age groups. This result indicates a widespread and consistent belief in AI's future impact, as professionals from all generations agree that the industry is more likely than not to be transformed by this technology. Whether a professional identifies as a typeface designer, a graphic designer, a font engineer, or a font developer, they all share the same fundamental perspective on automation tools.

3.3. Skepticism Expressed Towards AI: Ethical Issues and Corporate Dominance

When addressing the possible use of AI for core type design tasks, qualitative answers paint a picture of guarded skepticism with respondents commonly describing current AI tools as “imprecise,” “unpredictable” or “not ready for production.” Respondents further voiced three recurring concerns that echo wider debates in the creative industries:

- Intellectual property issues: the datasets used to train LLMs are likely to contain copyrighted typefaces used without permission from the original designers or type foundries.
- Energy consumption and carbon cost: the environmental footprint of large-scale inference was frequently cited as a deterrent.
- Opacity: designers mistrust what are seen as “black box” systems whose decision-making logic cannot be tracked or corrected. “Coding is the one area where I can see myself using AI automation, to help in building tools of my own design. I use a lot of non-AI automation in my workflow, but I can trust its output as I know what code I wrote and it is not going to hallucinate answers” (P263).

These (legitimate) concerns partly explain the community’s preference for deterministic tools, which offer much greater transparency at this stage, and require fewer resources.

A small but vocal group of respondents warn that the next wave of AI could entrench the power of corporations that already own extensive libraries of licensed fonts. They fear that companies such as Monotype or Google will “acquire the legal right to train an AI model on their library’s font data” and then offer “fully bespoke generated fonts at a fraction of the cost and time of a human designer” (P58). One respondent anticipates that the technology will simply magnify existing market imbalances: “It will be used by huge companies … that are already changing (harming) the industry in many ways. Only the means will change” (P304).

Beyond outright market domination, respondents see a subtler threat to the values of their craft, with eight participants predicting that profit and speed will eclipse quality and originality once AI-driven generative tools become mainstream: “People will choose convenience over quality” (P30). One respondent expects that cost savings will prove “too hard to turn down for clients” even if the results are mediocre (P58). Several foresee a deluge of derivative work: “Someone will make a model that generates typefaces … trained on fonts of poor quality and ethically dubious originality. Most people won’t know the difference and will pay £5 for a ‘custom font’” (P133). The likely outcome is that “mediocre work [will] pay even less” (P151), making it harder for independent designers to sustain their practice.

In that scenario, craft itself may become a mark of distinction. As one participant suggests, “There is always a connotation of premium or exclusivity when something is hand-made … perhaps there will be such a distinction for digital works as well” (P93).

3.4. Retaining Creative Control

A clear hierarchy emerges from the Likert scale questions concerned with respondents’ propensity to automate specific tasks. Tasks perceived as being key to the creative process attract the strongest resistance to automation, whether AI-based or not (Figure 13). These tasks include:

- Gathering references
- Sketching ideas
- Drafting the basic alphabet
- Extending glyphsets
- Marking up proofs

Only 22% of respondents state they are “very likely” or “extremely likely” to entrust the drafting of the basic alphabet to deterministic tools, and a mere 9% to AI-powered tools. Qualitative comments reinforce this pattern, with many respondents emphasizing the pleasure they derive from drawing (35 mentions), sketching (26), and exploratory design work (23). The respondents explicitly identified “the design process” or “creative part” as the heart of their practice, with six framing this territory as “decision-making” that must not give way to an algorithm. As one respondent remarked: “I started drawing type with a fascination for its formal qualities and craft-related aspects and skills. My personal interest in type design is about exploring one’s mind and its connection to the hand and eye. I have no real interest in having something else make decisions for me within this process” (P205).

Furthermore, five respondents praised the inherent slowness of type design, including:

> The slowness of type design is also what makes it enjoyable, therapeutic and gives a stronger sense of satisfaction once you reach a result you like (P31).
>
> Type design is a slow process. In my professional practice, I try to incorporate aspects of it in every project, whether a couple of letters for an identity or an entire alphabet. It’s something I particularly enjoy and which gives sense to my entire practice. I don’t think the world is in need of another thousand fonts and those produced should be carefully crafted and thought through (P56).
>
> Saving time is not key because the maturation of a font takes time—for good ones at least (P63).

In line with the above, respondents frequently highlighted the early stages of defining a typeface's identity as particularly enjoyable: finding references and gathering inspiration (4 mentions), defining the concept (6), mapping the family or design space (6), designing the core alphabet or basic glyphset (13), designing the extended or entire glyphset (7), applying optical corrections or refining shapes (6).

Interestingly, spacing was mentioned 13 times as an enjoyable task that should not be delegated to AI, indicating that respondents drew a clear distinction between spacing and kerning. Six respondents specifically named kerning as an enjoyable task that they would not delegate to AI, although, as we shall see below, this view is not reflected in the quantitative data.

Although most practitioners reserve the early, exploratory phase to human work, a small cohort of respondents (seven) view AI as a catalyst for creative ideation, an instrument for "achieving results we could not imagine ourselves" (P14). They endorse AI systems as rapid, low-stakes sketching partners, useful "for testing … a weight or width for a new style" (P8), or "to explore different directions faster" (P145). Several respondents describe using machine output as raw material that can be subsequently refined: one appreciates AI's capacity "to explore the project boundaries and to produce shapes that can be re-incorporated … after some edits to the 'proper' design" (P223). Others regard it as a provocation, for instance to feed LLMs with disparate historical samples "just to see how it [is] digested … before starting a new drawing" (P208). One respondent notes that such tools let them "create things [they] would not otherwise create" (P279). Together, these voices suggest that, in limited hands, AI can function less as an autonomous designer and more as a brainstorming companion.

3.5. Potential for Automating Technical Tasks Using AI

By contrast, enthusiasm for automation grows steadily as tasks become more technical or repetitive (Figure 12), such as:

- Optimizing font rendering
- Generating proofing documents
- Kerning
- Programming
- Writing OpenType features
- Setting vertical metrics and font info

These results resonate with respondents' qualitative responses, which highlight throughout the survey their willingness to remain in control of key creative labor and decisions. Many use or wish for tools that streamline these routine jobs to speed up the process, while requiring human control and adjustments. Automation is seen as a way to free designers from "boring work," allowing them to focus on the artistic side.

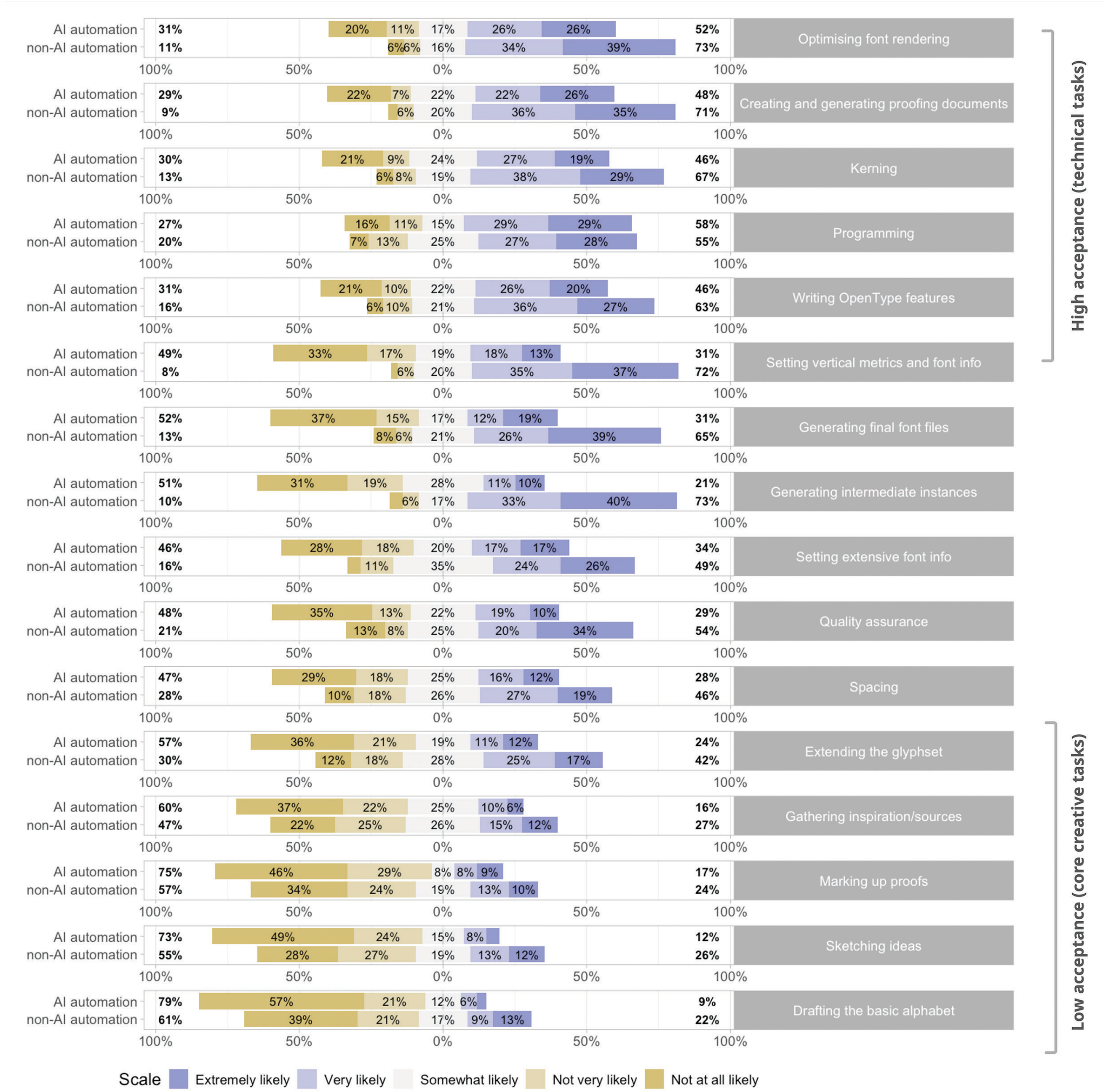

Figure 12. Likert scale on propensity to automate specific tasks using AI versus non-AI (deterministic) tools. Tasks are ranked from highest to lowest overall acceptance, separating high acceptance for technical tasks from low acceptance for creative tasks (*n*=89).

> It's important that we look at AI and automation as assistants to a designer and not the replacement of the designer. For the sake of our industry, AI should not be the answer to lack of creativity but rather as a way to improve efficiency (P108).

> I hope and believe that AI will make type design easier and largely eradicate tedious tasks such as setting vertical metrics and producing spacing/kerning. The type designer will still however rely on a good eye to quality assess the machine's quality assessments (P31).

> I hope it will help font developers to make repetitive work quicker (see kerning, accents, etc.) but not affect the drawing part too much, where, in my opinion, it should play only an assistive role. My dream is to use AI in the testing environment, such as proofing and checking, where sometimes you can easily make mistakes just because you're too tired to look again at the same thing for so long (P218).

For tasks traditionally regarded as repetitive rather than creative, respondents expressed markedly greater confidence in deterministic automation than in AI-driven solutions. For example:

- Setting vertical metrics and font info tables: 72% of respondents were "very" or "extremely" likely to use deterministic tools, compared with 31% who would choose AI.
- Generating intermediate instances: 73% were "very" or "extremely" likely to rely on deterministic tools, versus 21% for AI.
- Spacing: only 10% were "not at all likely" to automate spacing with deterministic tools, in contrast to 29% for AI.
- Entering extensive font info data: 3% were "not at all likely" to automate this task via deterministic tools, in contrast to 28% for AI.
- Quality assurance: 54% were "very" or "extremely" likely to use deterministic tools, compared with 29% for AI.

Spearman correlation analyses indicate that attitudes toward AI automation are strongly inter-correlated, reflecting an "all-or-nothing" approach, suggesting that those receptive to AI tend to be receptive across the board. In contrast, attitudes toward deterministic automation tools are compartmentalized and task-specific, indicating a more pragmatic "task-by-task" adoption. Designers' longstanding familiarity with deterministic scripting likely underpins this asymmetry. AI tools, by contrast, are not yet widely integrated into everyday workflows and consequently attract greater caution.

3.6. Kerning as a Candidate for AI Automation

Kerning emerged from the survey as the foremost candidate for further automation, with 44 respondents identifying it as the task they would most readily delegate to AI (provided the output met satisfying quality standards). This preference likely reflects current practice: deterministic tools such as Kern On (Figure 13), MetricsMachine and the third party service iKern (iKern, n.d.) already handle much of the kerning workload for many foundries and type designers. The perceived benefits are foremost efficiency and consistency with one respondent observing that kerning "is quite tedious and time-consuming, and even when I do it myself, I don't feel totally confident about the result, so I would gladly trust an AI to do a better job" (P24). Another described it as "repetitive, error prone" (P133), implying that assistance can raise, rather than lower, consistency and overall quality standard.

Nevertheless, this enthusiasm is tempered by a desire to retain final control, with numerous respondents calling for a hybrid solution in which the machine suggests kerning values, while the designer approves them:

> Yes, I believe AI can easily handle kerning and production, but I would always double-check and never publish a font without ensuring every detail aligns with my intentions (P38).

Some argued that kerning serves a secondary function as a systematic review of a completed typeface. Interviewees Cem Eskinazi and Emilios Theofanous both stressed that the kerning stage acts as "a good QA moment"* and "an opportunity to run the final checks,"† underlining its role in the broader cycle of quality assurance, rather than merely spacing adjustment.

Two ongoing experiments with AI-powered kerning exemplify this assistant model. The MILK prototype, developed by the independent collective type.tools (Type.tools, 2020), and an experimental plug-in by Tal Leming (with assistance from computer scientist Lars van Blokland), both employ machine-learning to suggest kerning pairs. Leming emphasizes that the aim is to build "an assistant, not a black box," noting that kerning is a subjective process that ultimately embodies "opinion" rather than immutable rule. From a technical standpoint, both teams report that the core modelling challenges are largely resolved, but some crucial outstanding issues remain that relate in large part to economics and ethics: the commercial market for professional kerning tools is modest, and few industry actors can absorb the costs of bringing such software to

* Cem Eskinazi interview.

† Emilios Theofanous interview.

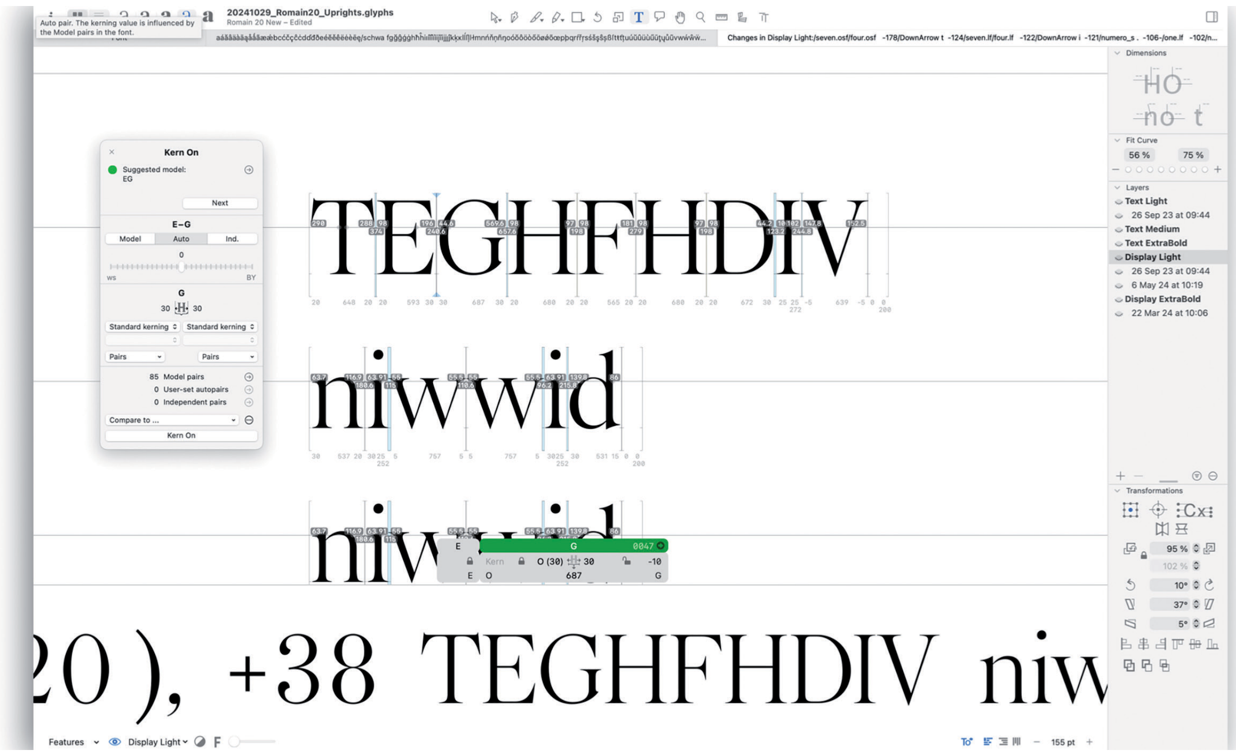

Figure 13. Screenshot of the Kern-On plug-in for partially-automated kerning of a typeface in the Glyphs font editor. Screenshot by the authors.

market; moreover, the energy required risks contradicting the efficiency gains that such an automation tool promises.

Taken together, these findings suggest that kerning should be considered not solely as a mechanical operation, but rather as an integral component of the design process. Designers seem to be willing to accept assistance as long as it optimizes their time, remains transparent about the process, and preserves their judgment and responsibility. The specific case of kerning therefore illustrates the broader argument articulated in our study, which is that automation is much better accepted when it supports and augments (rather than displaces) the designer's decision-making process.

3.7. Learning by Doing: Acquiring Skills Through Repetition

Automation bears with it the promise to relieve designers of time-consuming chores, but its indiscriminate adoption also risks affecting the very routines through which expertise is acquired. One respondent to our survey articulated this dilemma:

> ...only doing something repeatedly makes you good at it and allows you to create novel and truly innovative things. Without that learning, it is difficult to imagine something amazing being developed. But if AI does all the generic work, how can anybody learn the skills that make a good designer? (P116)

Another linked the problem to tool making itself:

> You can only write the tools you need if you fully understand what they need to do… Delegating things to AI is a magical thinking: "I cannot be bothered to figure this out, but I demand that it be done anyway" (P97).

Similar concerns have arisen in other fields; for instance, a recent article in *Le Monde* reported on French law firms, observing that LLMs already outperform junior solicitors for some administrative tasks and documentary research (Thomas, 2025). Yet it is precisely through this foundational, day-to-day work that young lawyers acquire the analytical discipline and knowledge on which their future careers depend.

Likewise, the cognitive process involved in designing typefaces appears to depend on iteration. Richard Sennett captures this point when he asks whether the machine is "a friendly tool or an enemy replacing the work of the human hand," concluding that "making is thinking" (Sennett, 2008, pp. 65, 81). Type designer Gerard Unger echoed this sentiment from within the discipline, arguing in 1982 that he preferred tools "that *help* [him] think rather than those that *make* [him] think" and refusing to become "a parameterizer" (p. 354).

Sennett (2008) argues that "skill development depends on how repetition is organized" (p. 38), something that resonates with the type design activity. Each cycle of spacing, proofing or curve-correction feeds tacit knowledge back into the next design decision. If you remove this cycle, the feedback loop collapses. Some form of repetition is therefore necessary, whether executed with a pen, a Bézier handle or an AI assistant. Even tasks that might appear repetitive and boring may eventually carry satisfactions of their own—something described by British book designer David Pearson (2024) as "the pleasure of gently nibbling away at something" through slow, repetitive labor.

Tal Leming voices a related concern when reflecting on his own software:

> Young designers at Font Bureau* used to get typefaces ready for interpolation… I wonder, did I fundamentally break something [when I wrote Prepolator]? I don't think that I did, I think economics played a bigger role than me figuring out how to calculate something. Kerning is a task given to assistants, who are still learning, in many foundries. Am I replacing it? I have deep ethical concerns about it.

* FontBureau was an influential early digital type foundry set up by type designer David Berlow (previously Mergenthaler, Linotype, Bitstream) and publication designer Roger Black in Boston in 1989. Its work influenced the industry through the designs it produced and the designers that came through and out of the firm (Fonts In Use, 2025).

The challenge therefore might lie in designing systems that support this learning process rather than supersede it, and in devising tools that invite experimentation and allow practitioners to grow from mechanical tasks to refined judgement. While automation may accelerate production and mask complexity at the same time, it could risk creating a generation of "parameterizers" (or one could say here, of "prompters"), removed from the skills that give the profession its distinctive value.

3.8. New Capabilities that Could Be Supported by AI

Survey participants suggested further areas for automation beyond kerning, and their responses list chores that are perceived as labor-intensive or technical:

Frequently cited were hinting (13 mentions), extending glyphsets (10), spacing (10), mastering/generating font files (7), vertical metrics (8), QA (5), generating text strings/proofing documents (6), adding font info (5), writing OpenType features (4), ensuring cross-platform compatibility (6), scripting/development (2), outline cleaning/refinement (3), and fixing interpolation issues (1). Drawing italics was mentioned twice, an activity that touches more directly on letterdrawing; however designers already have access to tools that derive an oblique from a slanted Roman style.

Interestingly, most of these operations are (at least in part) already handled by deterministic automation. The prevalence of such examples suggests that respondents are currently projecting familiar forms of automation onto AI, rather than envisioning new capabilities. But this tendency is likely to change as tools using machine learning mature.

Nevertheless, a handful of comments point beyond current routines: one respondent envisaged an assistant that would mediate between type designer and end user, "saving the user hours of type education" for instance by offering context-sensitive advice on stylistic sets (P8). Another wrote that he would welcome a tool that "keeps track of all the decisions made during the design process and checks if their application remains consistent" (P273) while another would like a tool that verifies technical compliance with specific environments such as Microsoft Office (P101).

The most ambitious proposal is a system able to extrapolate an entire font from a small set of key characters—an idea which, if successfully implemented, would be hailed by some as a breakthrough and by others as an existential threat:

> It would be nice to design the key characters… and let a tool expand them to derivatives. But also be able to teach the tool how you would like the derivatives to look (P135).

> I would like to automate drawing all those symbols which are not important for the design or look the same in most designs (like math symbols). Currency symbols are also no fun to draw and could be automated (P222).

> Drafting an additional master based on an existing master (such as bold, slanted, etc.). Maybe AI can do a better job at extrapolating than conventional tools (P221).

> Drawing based on a handmade sketch, finalizing letters, adding currency symbols, and other elements essential for a complete glyph set... I feel that the main characters are the most important, while the rest is more technical (P219).

Experimental platforms, including Typograph.studio and Monotype's Human Types and AI project (see footnote 3; Monotype, 2025; Monotype, n.d.-b), have already started to explore such functionality, but none yet is publicly available at the time of writing. Some respondents extended the concept to script expansion: one respondent envisaged rapid generation of CJK glyphs once the "design direction is set for key characters" (P93), while another would like to be able to add Arabic, Hebrew or Vietnamese ranges based on a Latin character set (P293).

The prospect of automated glyph expansion raises a number of concerns dealing with intellectual property, since the legal status of the libraries used for training remains unresolved. It also brings about questions of authorship, with the reservation of respondent P135 above echoing a more widespread reservation against computer-generated type design: that it would be faster to draw a typeface than to describe parametrically all detail decisions. The same notion, but within the field of programming itself, is expressed by programmer and consultant Kevin Henney (2009): "The act of describing a program in unambiguous detail and the act of programming are one and the same." And without an infinite amount of direction, who is really the author of the resulting shapes?

An AI typeface synthesizer can be imagined to create a possible shape of a letter to match a provided partial character set based on training data, that is to say: in a plausible, standard way. But would it be likely to exactly respond to the designers intent and every formal aspect specific to this unique typeface? Create something new on purpose? Or would it more likely simply propagate biases in standard maneuvers and recipes? The idea of autocompleting partial character sets therefore also raises the issue of script equity, as models trained predominantly on Latin data risk perpetuating existing cultural imbalances. As Borna Izadpanah wrote:

> One of the crucial questions is whether these technological advancements will support the increasing diversity we are witnessing in type design. Will these tools continue the trend of disproportionately Latin-centric developments, reinforcing Euro-centric knowledge structures? Or will they place more emphasis on other world languages and writing systems? The risk is that AI-based tools will be

> trained primarily on Latin script due to the abundance of available data, while other world scripts remain underdeveloped and underserved.*

4. Conclusion

In conclusion, our research indicates that deterministic automation is embedded in the type design industry, whereas AI-driven tools must still demonstrate their relevance, reliability and transparency, especially with respect to the provenance of training data. Practitioners are determined to retain control over the creative core of their workflow, particularly the drawing of letterforms, yet they are willing to delegate labor-intensive tasks such as kerning and font rendering optimization. Respondents stress that designers should keep final decision-making authority, and weigh any technological gain against ethical considerations. The absence of market-ready AI applications specific to typeface design undoubtedly underpins current skepticism. Nevertheless, general purpose LLMs, which are already competent at writing code and text, have already been adopted by a sizable minority of practitioners for peripheral activities such as script writing and proofing document generation.

Overall, the successful integration of automation into type design practice appears to depend on maintaining an appropriate balance between preserving creative authorship and key design decisions, while delegating routine technical operations to trustworthy software. Our findings also temper enthusiasm for wholesale automation, as iterative routines are not merely production steps but they are also the very means through which designers acquire tacit knowledge, and sharpen their judgement. If these cycles are removed entirely, the feedback loop that sustains expertise may wither. Therefore, the real balance could lie in developing tools that accelerate routine operations while encouraging experimentation and gradual mastery, rather than reducing designers to operators of opaque processes.

It should be remembered as well that these findings reflect the views of professionals whose expertise and livelihoods derive from the craft of type design. A wider population of font users—those who do not depend on designing and distributing typefaces for their income—may take a different view and positively welcome the prospect of generating complete fonts at the touch of a button. One participant succinctly captured the urgency of this shift, stating that:

> …as an industry, we need to be prepared for a near future where AI starts to become actually useful for the kind of work we do, as well as a world where

* Borna Izadpanah, email correspondence with Alice Savoie, February 10, 2025.

anyone who can instruct an AI can generate a usable font. Figuring out what that means to us is tremendously relevant (P124).

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