Adapting Saxophonists', Flutists', and Clarinetists' Expertise to the Karlax DMI Mediated by Neural Networks

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Abstract

This article presents a research creation project on the use of machine learning in the performance of digital musical instruments (DMIs), with a particular focus on adapting the expertise of woodwind instrumentalists to the digital instrument Karlax. The latter resembles a clarinet and contains several sensors: ten continuous keys, eight pistons, a rotary axis, and an inertial measurement unit. This project presents strategies for adapting the fingering, articulation, and timbre-control techniques used by clarinetists, flutists, and saxophonists to the Karlax, using neural networks. A software program called *Karlwind* in Max/MSP, which allows users to choose among three fingering configurations—*Karlsax*, *Karlflute*, and *Karlinet*—and several instrument presets, is introduced. The article presents briefly instrumentalists' feedback from etudes composed by the authors of the article. The article discusses the affordances of machine learning in this context.

1 INTRODUCTION

Developed in the early 2010s, the Karlax[1] is a clarinet-shaped digital musical instrument (DMI) equipped with various sensors, including ten continuous keys, eight pistons, a rotary axis with two bends, and an inertial measurement unit. It has been praised for its technical and design qualities (Mays & Faber, 2014) and its potential for developing an idiomatic and educational repertoire (Paine, 2015). It brings together an active community of performers and composers, proposals for notation systems, and a number of pieces (Lavastre & Wanderley, 2021). Unlike digital musical instruments such as wind controllers (Akai's EWI, Roland Aerophone, etc.) which mimic the design of wind instruments, the Karlax does not have breath sensors. Its hybrid design, partly inspired by wind instruments, a cylindrical body held with both hands with keys and pistons, makes it particularly appealing to instrumentalists such as clarinetists or saxophonists.
Despite this, there are very few pieces that use specific wind instrument techniques for mapping with the Karlax. A digital musical instrument (DMI) is commonly defined by three components: the interface equipped with sensors, the sound generator, and the mapping strategies that associate data from the interface with sound synthesis parameters (Miranda & Wanderley, 2006). To generate data inspired by wind instrument fingerings using Karlax, significant conditioning steps would be required: specifically, converting keys with continuous responses into discrete values and then generating different conditions based on key combinations.[2]

Machine learning using neural networks offers significant advantages for mapping with digital instruments. This involves, for example, training models (multi-layer perceptron or MLP) using pairs of input data (data from the interface's sensors) and output data (sound synthesis parameters) through a technique known as regression. In prediction mode, this technique allows for recalling states or interpolating between states by activating the interface's sensors. These techniques were developed as early as the 1990s (Lee et al., 1991) and are now commonly used in digital musical instrument performance with significant critical attention (Caramiaux & Tanaka, 2013) (Fiebrink & Sonami, 2020). These techniques are described as offering robust, fast, and simple means for creating mappings and enable a creative approach through various techniques such as underfitting, adding noise to datasets, or adding incoherent data. Exploring intermediate values and beyond proves particularly interesting for a creative approach (Fiebrink & Caramiaux, 2016). Furthermore, artistic "human" choices related to model training and their integration into the overall system remain essential (Gillies et al., 2016).

This study proposes adapting the playing techniques of saxophonists, flutists, and clarinetists to the Karlax using neural networks. We developed various software instruments incorporating machine learning for mapping fingering-pitch relationship, as well as for shaping timbre. These steps were carried out in collaboration with professional instrumentalists: one saxophonist, one flutist,

[1] www.dafact.com
[2] The piece *Ritual* for solo Karlax (2015) by composer D. Andrew Stewart features key combinations used as discrete signals, though it is not related to the fingering of wind instruments.

and one clarinetist. The article also presents *Karlwind*, a Max/MSP patch containing various instrument presets based on pitch/fingering configurations. The creative part of this project involved composing short pieces for a duo of two Karlax using *Karlwind*, which we rehearsed with the musicians. The article describes the choices regarding model training strategies, as well as mapping and sound synthesis strategies, and the feedback from the instrumentalists.

2 OBJECTIVE

The main goal of this project is to evaluate the potential of multilayer perceptron regressors as a tool for adapting the playing techniques of saxophonists, flutists, and clarinetists to the Karlax. This includes fingerings recognition, articulation, and timbre control.

3 METHODOLOGY

The project unfolded in three phases. For each phase, sessions were organized with professional musicians who had never played the Karlax before. These musicians—one saxophonist, one flutist, and one clarinetist—did not play the Karlax between sessions either. The sessions with the instrumentalists took place over several two-hour sessions. During the first two phases, the sessions were one-on-one, and we met with each musician twice (six sessions in total). The third session consisted of a workshop featuring short pieces composed by the authors of this article, with the same flutist and clarinetist as in the first two phases. All sessions were recorded on video, along with the computer audio outputs.

3.1 Fingerings recognition

The first phase involved adapting the fingerings of the alto saxophone, the C flute, and the B-flat soprano clarinet to the Karlax using a neural network (MLP regressor). At the end of this phase, three preliminary mapping configurations were proposed—named *Karlsax*, *Karlflute*, and *Karlinet*—and implemented in a Max/MSP patch. The first session with the performers mainly involved introducing them to the interface and validating the fingerings we had programmed with them. They suggested corrections during the first two phases.
The first step was to train models based on the fingering patterns of wind instruments adapted for the Karlax using an FM synthesizer. We asked professional performers to review our choices. Since there is no breath sensor, we adjusted the mapping so that the Karlax produces sounds when the keys are pressed, like a keyboard. Keys activation has replaced the covering of holes in wind instruments. The lowest register of the saxophone, flute, and clarinet is played using keys activated by the little fingers of the right and left hands. These keys allow for all melodic combinations between notes of the chromatic scale, as well as trills and bisbigliandi when activated repeatedly. Similarly, the Karlax features keys played by the little fingers of the right and left hands. To adapt the fingerings of saxophone, flute, and clarinet, for all melodic combinations, various configurations were devised by combining the action of keys and pistons of the Karlax.

Also, we have adapted the multiple fingerings that produce the same note using the combination of keys and pistons that seemed most natural to the players. The octave key on the saxophone and the twelfth key on the clarinet—which are normally played by the thumb of the left hand at the back of the instrument's body—are replaced by a piston pressed by the first joint of the right index finger (Figure 1).

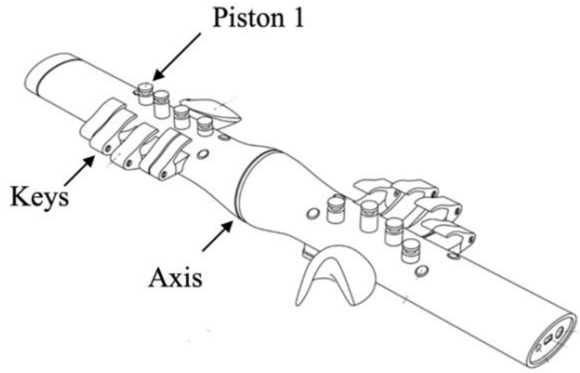

Figure 1: Top view of the Karlax. Activating piston 1 replaces the octave key on the saxophone and the 12th key on the clarinet.

3.1.1 Model training

We trained fingerings for the Karlax using a multilayer perceptron (MLP regressor): object [fluid.mlpregressor~] in Max from the FluCoMa Toolkit (Tremblay et al., 2022). We used key and piston values as input data (18 values in total), and the carrier frequency of an FM synth and general volume as output data (2 values). The fingerings were recorded with the keys fully depressed. The pistons that indicate velocity were converted to binary values of 0 or 1. We opted for a feedforward training approach with two hidden layers consisting of 12 and 5 neurons, respectively. We first trained the system on silence (volume at 0) with the keys and pistons deactivated for the instrument's lowest pitch. In predictive mode, this technique made it possible to reliably map fingerings to note pitches—including alternative fingerings—without any perceptible latency.

3.1.2 Sound morphologies

At this stage, several features have been added to improve the playing and listening experience. First, an algorithm for recognizing the velocity of the keys as they are pressed and released has been implemented. The faster the keys are pressed or released, the shorter the attack and decay, and the higher the amplitude (sustain). Additionally, the note duration— the time between note on and note off—is linearly controlled by the axis, ranging from a staccato playing style (closed axis) to legato (open axis). Activating the bend when the axis is closed gradually reduces the volume to 0. This axis also linearly controls an LFO. The more the axis is open, the faster the tremolo accelerates. Activating the bend when the axis is open generates a very fast LFO that resembles the frullatto technique used on wind instruments.[3] Finally, the axis controls the bandwidth of a filter (Q). The more the axis is open, the louder the sound and the wider the bandwidth.

3.2 Instruments creation

The second phase focused on timbre control, also using MLPs. This stage involved first developing software that houses the configuration (*Karlsax*, *Karlflute*, and *Karlinet*) and allows users to switch between sound configurations for seven instruments (sound synthesis + mapping). For this phase, we again presented the interface and its sensors to the instrumentalists and invited them to play the seven instruments (sound presets) without any specific instructions. When they felt they had finished exploring one instrument, we moved on to another. At the end, we asked them to sight-read simple, familiar melodies using the instrument of their choice, and we invited them to share their impressions and possible future developments.

This phase involved creating seven instruments (presets in Max/MSP). They use mapping techniques based on MLP regressors, as well as many-to-many mappings, and various sound synthesis types. These instruments can be played using the preliminary mapping that employs the fingering patterns for the saxophone and clarinet presented earlier. The goal was to offer musicians different gesture-sound relationships and to test the capabilities of machine learning in navigating timbre with the Karlax. The first three of the seven instruments produce sounds inspired by those of woodwind instruments, utilizing an FM synthesizer (Instruments 1 and 2) and Modalys (Instrument 3), a physical modelling synthesizer (Caussé et al., 2011) (Teglbjærg & Goepfer T., 2010). Instruments 4 to 7 use FM synthesis and the Surge XT hybrid synthesizer.[4]

3.2.1 Machine learning for timbre exploration

For instruments 4 to 7, an MLP regressor was implemented using the same [fluid.mlpregressor~] object, this time dedicated to the creative manipulation of the instrument's timbral behavior. This regressor maps data from the embedded inertial measurement unit (three axes of accelerometers and gyroscopes plus two axes of inclinometers), onto five parameters: the harmonicity ratio, two modulation indices of an FM synthesizer, the cutoff frequency of a filter, and the reverb amount.
Two distinct training approaches were employed. The first follows a conventional supervised strategy, where training points are deliberately chosen based on musical and timbral intent. The second leverages aleatory movement ([drunk] object in Max) through the parameter space, producing a more exploratory mapping.
In addition to the FM synthesizer, this second regressor also controls a parameter within the Surge XT synthesizer, loaded with a church organ preset. The timbral transition between the two engines is mapped onto the rotary axis of the Karlax. This choice serves a dual purpose: primarily, it acts as a timbral bridge, bringing the overall sound closer to that of the FM synthesizer and smoothing the transition between the two engines; secondarily, it introduces a more recognizable and acoustically familiar instrumental color, offering an alternative to the purely electronic character that FM synthesis alone tends to produce.

3.2.2 The software

Building on the MLP models and the feedback gathered during the first phase, the second phase focused on developing *Karlwind*.[5] Its user interface is deliberately simple and closed. It presents the performer with two dropdown menus: one to select the desired fingering configuration—*Karlsax, Karlinet, and Karlflute*—and another to choose the instrument preset (Figure 2).
The architecture of *Karlwind* is organized around three main parts: the conditioning of the Karlax's raw sensor data, the machine learning mappings, and the sound synthesis layer. Raw data from the Karlax's keys, pistons, rotary axis, and inertial measurement unit are first conditioned before being passed to the models. This includes converting continuous key values into ranges appropriate for fingering recognition, scaling inclination and axis data for dynamic control, and managing the binary state of the pistons. Audio activation and global output level are controlled directly from the main interface (Figure 2).

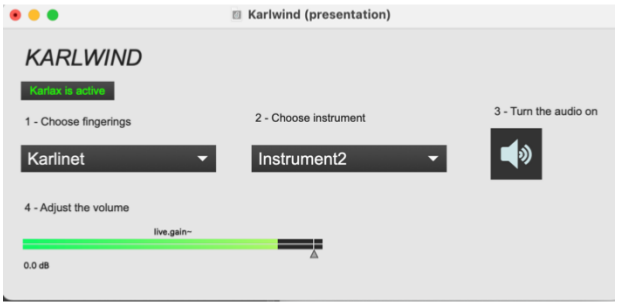

Figure 2: *Karlwind*: software that allows the user to play the *Karlsax*, *Karlinet and Karlflute* using various instrument presets (mapping + sound synthesis).

3.3 Composition of short pieces

The third phase involved composing six short pieces for two Karlax instruments: one in the *Karlflute* configuration, played by the flutist, and the other in the

[3] This option was developed by composer Tom Mays in his piece *Le Patch Bien Tempéré III* for flute, Karlax and electronics.

[4] https://surge-synth-team.org

[5] The Max patch called *Karlwind* called is available via the following link: https://github.com/KARWIND415/Karlwind

Karlinet configuration, played by the clarinetist.[6] The purpose of the session was to gauge professional musicians' reactions. A two-hour workshop was organized to rehearse the pieces. The scores were distributed a few days before the session with the instruction to read them on their respective instruments. The session involved practicing the pieces, presenting the composition projects, and discussing issues related to performance. A discussion with the musicians took place at the end of the session.

The six pieces present deliberately different approaches. First, the three pieces titled *Miniatures* composed by the second author focused on the possibilities of articulation: staccato notes, trills (Miniature 2 and Miniature 3), fingering: register shifts, arpeggios (Miniature 2 and 3), and glissando techniques (Miniature 1). They were composed as a duet for flute and clarinet without using *Karlwind*.

For example, Miniature 2, marked "as fast as possible", is a chromatic hocket of thirty-second-note groups and wide leaps that probes the resilience of the transferred fingerings at maximum velocity, where interpolation between adjacent positions is heard as articulation rather than as glissando (Figure 3).

Figure 3: Beginning of *Miniature 2* by Brice Gatinet

The three other pieces composed by the first author were created through experimentation with *Karlwind*. They are characterized by a freer notation style, including unmeasured sections, descriptions of the performer's gestures (fingering instructions and actions with the Karlax), and general descriptions of the sonic results.
In the piece titled *L'Oiseau goutte*, the *Karlflute* plays short, accentuated notes on Instrument 2 that sound like drops falling into a body of water. This metaphor is achieved through the glissando effects created when the performer lifts their fingers from the keys. The *Karlinet* part plays modulated and reverberated sounds on Instrument 5. By tilting the Karlax and pressing lightly on the keys, the performer can control the general timbre, especially the amount of reverb and modulation. The resulting sounds are a sort of crackling in the low register, "like whispers in the jungle" (Figure 4).

Figure 4: Beginning of the piece "*L'Oiseau goutte"* by Benjamin Lavastre

4 RESULTS

4.1 Affordances of Karlwind

Karlwind allows you to choose between two presets: first, the instrument selection, which defines the fingering-to-pitch relationship based on the saxophone, flute, and clarinet models; and second, the instrument setting, which defines the qualities related to timbre. In this sense, *Karlwind* offers several interesting features for performing with the Karlax, including glissandi, microtonal pitches, microvariations, and timbral navigation.

Glissandi
One of the consequences of using the MLP regressor is the interpolation between pitches when changing fingerings, resulting in glissandi. This is particularly noticeable when changing positions slowly. This feature offers several advantages. Even the slightest movement of the player's fingers on the keys affects the resulting sound, much like the variations that can occur when covering the holes on a wind instrument. Glissandi offer interesting articulation possibilities when fingerings are alternated rapidly (trills, ornaments, etc.).

Achieving the same result with conventional mapping would require significant data processing. The keys would need to be converted into discrete signals (a signal is generated when a key reaches a threshold value), and these signals would then need to be differentiated based on the gate-type key combinations. In this case, the key's travel would have no musical effect. Alternatively, a glissando effect could be implemented, which would also require extensive data processing to ensure that the key actions generate the desired interpolation.

These glissandi can be reduced using a training dataset in which the keys are not pressed all the way down. However, this solution was unsatisfying. It was necessary to collect datasets corresponding to different levels of key press depth to avoid glissandi, making the training tedious. This also reduces the articulation possibilities mentioned above.

[6] Excerpts of the rehearsals and scores of the six pieces are available at the following link: https://drive.google.com/drive/folders/1XFqLXhlNG2_cr4RJEQqPJlnCsoBD1318?usp=sharing

Furthermore, the glissando caused by the return to 0 when all keys are released seemed to be the most undesirable effect. This effect is particularly noticeable in the instrument's high register. To mitigate it, several techniques could be implemented. One solution would be to train different MLP models, each corresponding to a portion of the spectrum (one octave, for example). This would reduce the range covered by the glissando, but a suitable option would need to be found for the transition between the MLPs. Another option would be to constrain the resulting pitch when the volume level drops below a certain threshold. Finally, a third technique involves the performer closing the axis and activating the bend to cut off the sound, then releasing the keys.

Microtonal pitches
The use of the MLP also results in the appearance of microtonal pitches—either within or outside the trained register—when playing untrained fingerings. Model training plays a fundamental role here, as there can be significant variations in pitch depending on the model.

Microvariations
Finally, the use of MLP results in subtle variations in pitch and volume that would be difficult to achieve with conventional (many-to-many) mapping strategies. In this respect, it resembles playing an acoustic instrument, where it is nearly impossible to obtain the same sound with two similar gestures.

Navigating timbre
The timbral space, treated independently, is organized into zones that can be explored in a nonlinear manner. In instruments 4 through 7, maximum reverb is achieved by tilting the Karlax backward, while the strongest modulation—which produces a metallic sound—is achieved by tilting it forward. Interpolation in untrained zones and subtle movements lead to unexpected, yet still manageable, results. The trained model is stable, so the topography can be memorized and exploited with intent, allowing for progression.

4.2 Sessions

4.2.1 Impressions from instrumentalists

In all the three phases, the musicians generally preferred to play while seated, with the Karlax resting on their right or left thigh. They quickly got the hang of it, even though the handles on either side of the Karlax seemed restrictive at first glance. The saxophonist pointed out that when playing the saxophone, the right wrist is positioned above the fingers. This is not the case with the Karlax, given the current design of its handles. The transfer of fingerings from their instruments to the Karlax was viewed positively by the musicians. They noted that while there was a brief adjustment period, they felt comfortable with the interface and the fingerings. Pressing the keys to produce a sound in the manner of a keyboard felt quite natural to expert musicians. This observation is partly because part of their gestures involves pressing keys.
The new fingerings and the octave or twelfth key—which is activated by pressing the first piston with the first joint of the index finger—require a longer adjustment period. However, they all mentioned that it would become natural with practice. At first, the glissandi caused by the MLP were not perceived as a particular constraint. As the sessions progressed, the glissando that occurred when all the fingers were lifted emerged as a significant limitation.

Turning the axis to adjust the envelope, tremolo speed, and volume felt particularly natural to them and was considered an interesting feature. The musicians mentioned the importance of breath control, the action of the tongue, and the mouth in musical articulation with their instruments. The discussions focused on how these articulations could be adapted. It was particularly interesting to see how they intuitively sought out familiar sound patterns. For example, the flutist noted that it was natural for the most modulated sound, where the timbre is trained with an MLP, to be produced by making a downward gesture, whereas on the flute, the most turbulent sound is produced by directing the breath downward.
At the end of the rehearsal for the third phase, the duo preferred freer notation and a more gestural style of composition. They felt that this style was particularly well-suited to the Karlax. Conversely, they found the pieces with more conventional writings for flute and clarinet less interesting. Overall, they viewed the experience positively. They noted that, to take their interpretation further, they would need greater access to the Karlax.

4.2.2 Impressions from composers

The use of MLPs offers interesting compositional possibilities. It gives rise to new sonic behaviors that can serve as the basis for original musical ideas, such as crackling effects or "drops" (Figure 4). As we have used it, this mapping technique reflects the hybrid nature of the instrument's design. A compositional approach that subtly combines electroacoustic effects with broader gestures, alongside more idiomatic wind instrument techniques (such as fingerings and articulations), seems particularly appropriate.

5 DISCUSSIONS

5.1 Agency

Let's summarize the main advantages of using *Karlwind* with the Karlax. *Karlwind* allows for:

1. leverage the hybrid conception of the interface
2. efficient, rapid and robust adaptation of wind instrument fingering without noticeable latency, opening up new possibilities for articulation
3. the development of new and unexpected sonic behaviors that give rise to new ways of playing
4. a more organic, less linear performance (microvariations, exploration of "regions", etc.) that engages the performer more deeply
5. easy use of the Karlax with introductory playing modes for composers and performers

Issues, however, can arise. For example, retraining or refining the models can alter key musical characteristics, such as microtonal pitches (Laguna & Fiebrink, 2014). As part of this research, we deliberately chose to halt the development of the models at a certain stage of the creative process. Furthermore, the two model types corresponding to the first two phases pursued different objectives and employed appropriate training strategies. The first model sought reliability in recognizing the relationships between pitch and gesture, while the second focused on the performer's experience in navigating timbre.

Furthermore, it seems there are two options for improving *Karlwind*: 1. rebuilding or fine-tuning the models, or 2. shaping the results. To refine the model, we could use the options available with the object [fluid.mlpregressor~] object in FluCoMa. The activation function (@activation) is perhaps the most influential lever: different functions such as Rectified Linear Unit (ReLU), sigmoid, or tanh transform values differently and produce qualitatively distinct learned mappings, effectively changing the curvature of transitions between positions. The hidden layer structure (@hiddenLayers) further determines the complexity of the learned mapping: deeper networks with more neurons can model highly non-linear relationships between input gestures and output parameters, producing more expressive or irregular transitions. Finally, and perhaps most directly, the number and placement of training points in the dataset acts as the most immediate guide to interpolation behavior. Adding intermediate points steers the learned curve toward musically intended trajectories. The option of shaping or "sculpting" the results would involve identifying the relationships between gestures and sounds that seem most interesting and then highlighting certain aspects using traditional mapping techniques or by processing the output signal.

Many-to-many mappings could certainly reproduce the isolated effects produced by MLPs. For example, interpolations between notes that generate glissandi can be achieved using traditional mapping strategies. In the case of fingering recognition, it is the holistic and constrained approach that makes this mapping method particularly interesting. Also, our project remains relatively simple at this stage. This project does not involve dynamic machine learning that can adjust models' responses based on a performer's or a group's performance over time (Blanchard et al., 2024).

Beyond these technical considerations, the use of machine learning in this context opens a broader conceptual shift. Training a model across multiple simultaneous dimensions of sound synthesis parameters moves beyond the classical paradigm of many-to-many programmed mappings, which tend to reflect a human intuition constrained to two or three dimensions. By exploring a high-dimensional parameter space through both supervised training and aleatory movement, the system can discover and stabilize relationships between gesture and sound that would be inaccessible, or simply unimaginable through conventional approaches. This reframing of the mapping process, from deliberate construction to guided exploration, constitutes one of the most generative affordances of machine learning in the context of digital musical instrument use (Fiebrink & Caramiaux 2016). The performers' preference for a freer style of writing confirms this idea. As a consequence, *Karlwind* can serve as a basis for developing an idiomatic repertoire specifically conceived for saxophonists, flutists, or clarinetists approaching the Karlax (De Souza, 2017).

Karlwind redistributes agency unevenly across the system. The interface stays agentially neutral, transmitting gesture without the resistive feedback an acoustic instrument provides. Configuration — fingering system, preset — is fixed by the designer before playing, not by the performer in the moment. The trained models exercise the most autonomous agency: in untrained or interpolated regions, they generate sonic outcomes neither designer nor performer explicitly intended, producing the microvariations described in Section 4.1 (Morrison & McPherson, 2024). Correspondingly, the performer's agency shifts from directly producing sound to navigating and recalling a topography the model has already learned, echoing how sensor-based performance more broadly redistributes agency between performer and instrument (Tanaka, 2000). Karlwind's contribution to agency, then, lies less in new capabilities than in relocating where decisions happen in the gesture–sound chain — from real-time performer control to learned model behavior between trained points.

5.2 Accessibility

Accessibility is a crucial issue when it comes to digital musical instruments, particularly those with unique designs like the Karlax and limited production runs (Morreale & McPherson, 2017) (Marquez-Borbon & Martinez-Avila 2018) (Lavastre & Wanderley, 2024). There is a virtuous (or vicious) cycle that links numerous interfaces, users, and instrumental culture. A greater number of interfaces would attract more users, who would in turn expand the repertoire and playing techniques, reinforcing a virtuous cycle that draws in still more performers. If one wishes to take the next step in mastering a digital musical instrument, it seems wise to draw on the expertise of trained musicians, especially acoustic musicians (Cook, 2001). Acoustic instruments technique could be viewed as a reservoir of "economy of movement": maximizing musical possibilities with minimal amplitude, while digital musical instruments like the Karlax have built their reputation on their potential for ample gestural expression.

Karlwind allows experienced musicians to explore modes of expression that are often new to them and to discuss practical issues related to performing with digital musical instruments. The creative collaboration with the instrumentalists demonstrated that their feedback was crucial for validating certain compositional ideas. In *Instrumental Interaction III* for Karlax and guitar, the Karlax part was constructed based on the composers' intentions and the possibilities for interaction with the guitar, particularly in terms of sound synthesis (Lavastre & Gatinet 2025). This process makes the Karlax's role particularly secondary. *Karlwind* offers the opportunity to have musicians test the Karlax and identify interesting playing techniques to help shape the piece. This makes the Karlax more accessible to musicians—both instrumentalists and composers. The approach here is based on experimentation and feedback from the performers.

6 FUTURE WORKS

A logical next step for this project would be to validate this study by having other clarinetists, flutists, and

saxophonists try out *Karlwind*. It is naturally tempting to extend this study to other instruments and determine which techniques can be adapted to the Karlax. For example, one might consider other wind instruments such as the trumpet or the horn. Another area of research could focus on guitar-type instruments, which are also played with both hands. This research can also be transposed to other DMIs that feature original and hybrid designs, such as the Eigenharp, the T-Stick (Mallock, 2007), or the Meta-Instrument (Couprie, 2018). It could highlight the value of adapting expertise from acoustic instruments to digital instruments.
At this stage, the authors of this article would like to expand on this experimental approach by composing new short pieces / études and having them tested by performers. The specific techniques validated by the performers would serve as the foundation for more substantial compositions and would help identify appropriate notation choices.

As part of this research on wind instruments, a future development involves finding more convincing ways to adapt breath control and its possibilities for articulation. During this study, attempts to transfer breath-related behaviors onto the rotary axis and inclination sensors proved only partially satisfying, as the gestural logic of these sensors does not map naturally onto the physical and muscular experience of blowing into an instrument. The embodied continuity that breath provides in acoustic wind playing as a driver of volume, tone color, and musical phrasing remains difficult to replicate through postural or rotational gestures alone. Articulation presents an equally open and compelling challenge. In saxophone and clarinet playing, articulation is intimately tied to the placement and movement of the tongue on the reed. Exploring how specific key combinations, pressure variations, or rapid gestural transitions could serve as proxies for tongue articulation, and training MLP models to recognize and translate these gestures into corresponding sonic behaviors, represents an interesting direction.

These efforts toward more idiomatic breath and articulation control are inseparable from the broader question of idiomatic writing for the Karlax. As Huron and Berec (2009) suggest, idiomatic organization in music emerges from the affordances of the instrument and the embodied knowledge of its players. In this sense, developing a more nuanced emulation of wind instrument gestures within the Karlax's native interface would not only enhance the expressive capabilities of instruments such as *Karlsax, Karlflute* and *Karlinet*, but would also open new possibilities for composers. One could envision scores written specifically for saxophonists, flutists or clarinetists playing the Karlax that engage with the technical vocabulary of wind instrument performance while exploiting the unique sonic and gestural possibilities that machine learning mappings afford.

7 CONCLUSION

In this article, we presented a study aimed at adapting fingering techniques for the clarinet, flute, and saxophone to the Karlax digital instrument using neural networks (multilayer perceptron). Machine learning proved effective, first and foremost, in adapting the fingerings for the saxophone, flute, and clarinet to the Karlax. Building on this initial step, we developed instruments whose timbre navigation is also enabled by machine learning and had them tested by professional musicians.

This research also presents a software program: *Karlwind*. It allows users to choose between three fingering systems—*Karlsax*, *Karlflute*, and *Karlinet*—as well as seven instrument presets. These instruments enable users to explore creative playing techniques. The two authors composed six short pieces for *Karlflute* and *Karlinet*. Rehearsing these pieces helped identify specific techniques and compositional approaches aligned with the musicians' experiences and revealed appropriate types of notation.

ACKNOWLEDGMENTS

The authors would like to thank Alex Huyghebaert, Charlotte Layec, and Jean-Marc Bouchard for the time and engagement they devoted to this project and for their valuable comments. The authors would also like to thank the Center for Interdisciplinary Research in Music, Media, and Technology (CIRMMT).

AUTHOR DECLARATIONS

This research involved sessions with professional musicians who were informed of the purpose, procedures, and recording of the study prior to participation. All participants gave informed consent for the use of their performances, improvisations, and recorded sessions for the purposes of this study and its dissemination.

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