Developments in the Built Environment 27 (2026) 101022

Contents lists available at ScienceDirect

Developments in the Built Environment

journal homepage: www.sciencedirect.com/journal/developments-in-the-built-environment

# Toward intelligent construction: AI-driven autonomous monitoring of fresh concrete flow behaviour

Pengwei Guo [a], Le Teng [b], Neil Yorke-Smith [c], Sandra Barbosa Nunes [a,*]

[a] Department of Civil Engineering and Geosciences, Delft University of Technology, Stevinweg 1, Delft, 2628 CN, the Netherlands
[b] School of Materials Science and Engineering, Southeast University, Nanjing, 211189, China
[c] STAR Lab, Delft University of Technology, Delft, 2628 CN, the Netherlands

ARTICLE INFO

*Keywords:*
Concrete flow behaviour
Real-time monitoring
Artificial intelligence

ABSTRACT

Accurate assessment of the flow behaviour of fresh concrete is essential for ensuring stability, mechanical performance, and durability. Flow behaviour governs key construction processes including mixing, pumping, and placement. While rheometers provide precise measurements, they are costly, complex, and impractical for field use. Consequently, alternative techniques have gained attention for real-time and on-site monitoring. These approaches evaluate flow characteristics and track mixing by capturing measurable signals such as images, sound, vibration, or power consumption. Compared to rheometers, they offer advantages in speed, automation, and minimal disruption. This review critically examines the principles, accuracy, technology readiness, applicability, and limitations of these emerging approaches, and explores future directions. It also emphasizes artificial intelligence (AI) integration to enhance data processing and automation and examines multimodal strategies such as multi-sensor fusion, multi-source data fusion, and large language models to improve analysis and decision making. These advances support the vision of Industry 4.0 through intelligent and connected concrete production systems.

## 1. Introduction

The flow behaviour of fresh concrete is fundamental to modern construction, governing concrete's performance from mixing to placement and consolidation (Lomboy et al., 2014). This behaviour is primarily governed by rheological parameters such as yield stress and plastic viscosity, which influence not only the efficiency of mixing, pumping, and casting but also the stability of fresh concrete, including resistance to segregation, control of bleeding, and uniform dispersion of aggregates, admixtures, and fibres (Meng and Khayat, 2017a; Çelik et al., 2022). Ultimately, flow behaviour determines the mechanical performance and long-term durability of hardened concrete, underscoring the importance of precise control during the construction process for ensuring structural reliability and service life (Abrishambaf et al., 2022; Liu et al., 2023). Given that concrete is the most widely used construction material globally, effective monitoring and management of flow behaviour are essential for the development of advanced construction techniques (e.g. 3D printing) and structural applications.

Traditionally, the measurement of concrete flow behaviour relies on specialized laboratory instruments, such as rheometers (Du et al., 2023a). Rheometers offer precise and direct quantification of parameters such as yield stress and plastic viscosity, providing detailed insights into the flow characteristics of concrete (Feys and Khayat, 2013). However, the application of such instruments is limited due to their high cost, operational complexity, and tendency to interfere with the mixing process (Guo et al., 2022). Additionally, their size and sensitivity to environmental conditions restrict their use in field environments, where real-time decision-making is often necessary (Teng et al., 2020). Standard workability tests, such as the slump, flow table, slump-flow, and V-funnel tests, are widely used in practice and provide measures of concrete flow behaviour. However, they may be insufficient to distinguish between different types of concrete – for example, the slump test may not differentiate mixtures with similar yield stress but differing in plastic viscosity (White, 2025). In addition, each workability test is applicable only within a specific workability range, and these methods require interrupting the mixing process to extract samples, which limits their suitability for continuous monitoring (Fares, 2015).

To overcome these limitations, researchers have increasingly explored alternative sensing techniques to provide real-time monitoring of fresh concrete during mixing and handling. These approaches

* Corresponding author.
*E-mail address:* s.c.barbosanunes@tudelft.nl (S.B. Nunes).

https://doi.org/10.1016/j.dibe.2026.101022
Received 25 May 2026; Received in revised form 11 August 2026; Accepted 17 August 2026
Available online 17 August 2026

estimate the rheological behaviour of concrete by capturing various measurable parameters, such as visual images from cameras (Schack et al., 2024a), readings from torque sensors (Khayat and Libre, 2014), energy consumption monitored by power meters (Cazacliu and Roquet, 2009). By correlating these indicators with rheological properties, it becomes possible to monitor fresh concrete in real time with minimal interference to the material (Coenen et al., 2024). Such techniques offer advantages in terms of speed, automation, and adaptability, making them attractive for field applications in dynamic construction environments.

Monitoring flow behaviour after mixing is also essential, since defects such as segregation and bleeding compromise durability and mechanical performance (Benaicha et al., 2025). Traditional workability tests offer limited insight, whereas recent computer vision advances enable automatic and non-invasive evaluation. Schack et al. (2024b) applied deep learning-based segmentation to slump flow tests to quantify segregation and bleeding. The same group (Schack et al., 2024a) subsequently employed multi-view stereo to reconstruct three-dimensional slump flow surfaces for detecting aggregate agglomeration. In addition, a multi-sensor approach that combines 3D reconstruction and an accelerometer is proposed, in which 3D reconstruction is used to estimate yield stress from the final slump geometry, while the accelerometer measures cessation time to determine viscosity (White and Lees, 2025). These advances show that imaging analysis offers an effective toolset for quantitative evaluation of fresh concrete quality.

Despite the progress made, a comprehensive review that consolidates and integrates the existing knowledge in this field is still lacking. To address this gap, this review provides an overview of existing and emerging techniques for assessing concrete flow behaviour. It critically examines the principles underlying each method, evaluates their accuracy, robustness, and technology readiness level (TRL), and discusses their respective advantages and limitations. By comparing the current state of the art, the article aims to identify promising directions for future research and development.

In addition to reviewing sensing technologies, this article highlights the growing role of artificial intelligence (AI) in advancing monitoring systems for fresh concrete flow behaviour. AI-based techniques have demonstrated strong potential in enabling automatic feature extraction from complex sensor data (e.g., images, acoustic signals, or vibration patterns), and supporting robust predictive modelling of flow behaviours, such as rheological parameters. Furthermore, the recent emergence of multi-modal strategies that combine heterogeneous data sources, such as torque sensor signal with image-based features, provides new opportunities for knowledge discovery and intelligent data integration (Tahoun et al., 2021). By embedding AI and multi-modal technologies into flow behaviour monitoring, the construction industry can progress towards more automated, reliable, and sustainable concrete production and quality control. Emerging large language models and visual–language models enable multi-modal integration of images, signals, and text, offering new potential for automated interpretation and monitoring of fresh concrete flow behaviour (Kasneci et al., 2023).

The literature was primarily collected through Google Scholar, ScienceDirect, and Web of Science using combinations of keywords. The use of multiple databases and broad search terms was intended to minimize the risk of overlooking important studies. The core search string was (“fresh concrete” AND (“flow behaviour” OR “workability” OR “rheology”) AND (“artificial intelligence” OR “computer vision” OR “deep learning” OR “machine learning” OR “sensing technology” OR “sensor-based measurement” OR “mixing power” OR “image analysis”)). Publications from 2000 to 2026 were considered, and the first 50 records ranked by relevance for each keyword combination were screened. Studies directly related to the monitoring or prediction of fresh concrete flow behaviour, workability, or rheology using AI- or sensing-based techniques were retained. After deduplication and screening, 65 primary references were selected. In addition, targeted searches identified 10 supplementary references, including technical reports, standards, and relevant webpages, to complement topics not sufficiently covered by the primary literature.

The remainder of this article is structured as follows. Section 2 establishes the definitions and classification framework for concrete flow monitoring methods. Section 3 focuses on monitoring techniques applied during the mixing stage. Section 4 reviews post-mixing monitoring approaches used to assess flow behaviour after production. Finally, Section 5 summarizes the strengths and challenges of the existing methods and outlines future research directions.

## 2. Definition and classification

This section presents the general definition of concrete flow behaviour and the corresponding assessing methods. Section 2.1 discusses the rheological characteristics of fresh concrete, while Section 2.2 introduces the monitoring techniques used to evaluate concrete flow behaviour and classifies them into different categories.

### 2.1. Concrete flow behaviour

Fresh concrete exhibits complex non-Newtonian flow behaviour that cannot be adequately described by simple linear fluid models. Its rheological response is most commonly characterized by the Bingham model, which assumes that the material possesses a yield stress that must be overcome before flow can initiate (Khayat et al., 2019). In other words, concrete behaves as a solid-like material under low applied stress and begins to deform and flow only when the applied shear stress exceeds this critical threshold (White and Lees, 2025). A higher yield stress indicates a greater resistance to flow, thereby reducing workability and requiring increased energy for mixing and pumping of concrete (Xie et al., 2013). Proper control of yield stress ensures segregation resistance by maintaining aggregate distribution and preventing of paste bleeding (Yan et al., 2020), while in pumping it indicates the initial pressure required to mobilize concrete, affecting energy efficiency (Feys et al., 2022). Once yielding occurs, the relationship between shear stress and shear rate becomes approximately linear, and the slope of this linear region is defined as the plastic viscosity (Teng et al., 2020). Plastic viscosity reflects the resistance of fresh concrete to continuous flow after yielding (Mandal et al., 2023). Plastic viscosity influences flow resistance and energy demand during placement, thereby affecting operational efficiency. Higher values enhance the stability by reducing segregation and bleeding but hinder pumping and casting, while lower values improve flowability at the risk of heterogeneity and separation (Teng et al., 2020). The flow behaviour of fresh concrete is fundamentally linked to its workability, stability, and constructability in engineering practice. Therefore, effective control of flow behaviour is essential to ensure construction quality, operational efficiency, and long-term structural performance.

The flow behaviour of fresh concrete can be characterized not only by rheological parameters measured during mixing, such as yield stress and plastic viscosity, but also by post-mixing indicators that reflect stability and homogeneity. In addition to rheological parameters measured during mixing, post-mixing indicators provide complementary insights into the flow behaviour and stability of fresh concrete. Practical measures such as slump, slump flow spread, segregation resistance, and bleeding are widely used to evaluate workability and cohesiveness under field conditions (Bui et al., 2002; EN 12350, 2019a; EN 12350, 2019b). These indicators reveal critical aspects of mixture performance, including whether aggregates and paste remain uniformly distributed, whether excess water migrates to the surface, and how readily the mixture spreads under its own weight.

### 2.2. Flow behaviour monitoring methods

The classification of mixing-flow monitoring methods presented in this review follows the overall methodological framework adopted in the study. These methods are organized into three main categories: (1) Conventional offline post-mixing testing; (2) In-process (real-time) monitoring; and (3) Advanced post-mixing monitoring.

(1) **Conventional offline post-mixing testing.** The flow behaviour of fresh concrete is typically described by two key rheological parameters: yield stress and plastic viscosity. Instruments such as rheometers and viscometers remain the most widely used tools for characterizing these properties. Typical laboratory systems include parallel-plate rheometers such as Anton Paar MCR 302, which provide high-precision measurements for small batches of cement paste (Du et al., 2023b). Portable concentric-cylinder devices such as BTRHEOM offer similar capabilities for concrete materials under field conditions (BTRHEOM, 2004). For mixtures containing sand or coarse aggregates, larger-capacity concentric or coaxial cylinder systems such as the ConTech viscometer (Khayat et al., 2019) and the ICAR/ICAR Plus rheometer (Du et al., 2023a) enable reliable rheological assessment of mortar and concrete samples. These types of equipment provide direct measurements of material flow properties and establish the fundamental understanding required for evaluating flow stability, mixture optimization, and quality control. Standard workability tests also provide alternative approaches for estimating rheological properties. For example, a theoretical model was proposed by Meng et al. (Meng and Khayat, 2017b) to estimate the yield stress of cement paste based on the final spread diameter obtained from the slump test, establishing a quantitative correlation between yield stress and spread diameter. The same study also identified a relationship between the plastic viscosity of concrete and the V-funnel flow time for self-consolidating mixtures (Meng and Khayat, 2017b). In addition, the vane test and the inclined plane test have proven effective for assessing the static yield stress of cementitious materials (Omran et al., 2011; Jarny et al., 2008).

(2) **In-process (real-time) monitoring.** To capture the dynamic evolution of concrete flow during mixing, real-time sensing technologies have been increasingly researched. Devices such as video cameras, audio sensors, and vibration signal recorders enable continuous monitoring of the mixing process by analyzing visual patterns, acoustic signatures, and vibration responses. These methods provide valuable insights into aggregate movement, lubrication layer formation, and the early detection of abnormal mixing behaviour. However, these data are not directly correlated with flow behaviour, as they serve only as indirect indicators rather than explicit rheological measurements. Moreover, the analysis typically relies on manually designed features or predefined statistical metrics, which limit their ability to represent the complex, time-varying nature of concrete flow. This gap has highlighted the need for advanced data-driven approaches, and AI has emerged as a promising tool capable of learning hidden patterns from multimodal sensing data and establishing more direct links between sensor observations and flow behaviour.

(3) **Advanced post-mixing monitoring.** Post-mixing assessments focus on evaluating flow-related characteristics after mixing has been completed. Technologies such as 3D scanners can rapidly reconstruct the surface geometry of the mixed material, capturing indicators of flow uniformity, segregation, and surface texture. When combined with sensing techniques and data-driven analysis, these post-mixing methods enable fast, automated interpretation of flow behaviour, reducing the time required for traditional rheological testing. By providing quick feedback on mixing efficiency and identifying potential issues immediately after mixing, these approaches help streamline the evaluation process and support more efficient decision-making in practice.

## 3. Monitoring of flow behaviour during mixing

This section reviews in-line methods for evaluating the flow behaviour of concrete during mixing. Section 3.1 presents power and torque monitoring, Section 3.2 introduces vision-based techniques, Section 3.3 covers audio-based analysis, and Section 3.4 discusses vibration analysis.

### *3.1. Mixing resistance measurement*

#### *3.1.1. Mixing power*

Power measurements are cost-effective and non-invasive methods for assessing the force needed to rotate an impeller shaft (Cazacliu and Legrand, 2008). A wattmeter can be connected to the mixer's motor to record power consumption as an indirect measure of mixing resistance. Cazacliu and Roquet (2009) proposed a model linking power curves to mixing kinetics, identifying five characteristic stages (dry powder, dry granules, wet granules, granular suspension with agglomerates, and fully dispersed suspension), as shown in Fig. 1. Two key transition points were defined: the maximum cohesion point (wet granules to hard paste) and the fluidity point (hard paste to suspension). The fluidity point proved a practical indicator of mixing difficulty and homogeneity, demonstrating that power monitoring offers a reliable in-line method for controlling and optimizing concrete mixing. Concrete was considered homogeneous once the power consumption curve reached its fluidity point (Chopin et al., 2007). Ngo et al. (2016) further demonstrated that mixing power curves could be used to monitor water content in concrete production. Tests on 40 industrial batches showed that the fluidity point on the power curve reliably indicates homogeneity, with water prediction errors within $\pm 3.8$ L/m$^3$, and its identification determines the end of mixing, reducing average mixing time by up to 16%. This confirms that mixing power is a reliable, non-invasive method for water control and process optimization in concrete plants.

Chopin et al. (2007) investigated the relationship between mixer power consumption and concrete homogenization. Power consumption was recorded using a power meter on the drive system of the mixer to generate power consumption curves, while rheological properties such as yield stress and plastic viscosity were measured using the BTRHEOM rheometer. Power consumption was recorded at various mixing durations (20, 38, 55, and 600 s). For a given mixture, the results indicated that the rheological parameters, including yield stress and plastic viscosity, remained relatively constant as mixing time increased during the homogenization stage (stabilized power consumption). The final stabilized power consumption strongly reflected the yield stress and plastic viscosity, supporting the idea that power consumption is influenced by the torque required to overcome the material's resistance. This confirms that power input depends on both yield stress and plastic viscosity. Consequently, the mixer can be interpreted as a large-scale rheometer capable of indirectly assessing fresh concrete rheology. The findings also suggest that mixer design affects homogenization efficiency, with larger mixers requiring shorter mixing durations to reach a steady state. Hayano and Kudo (2021) proposed a machine learning–based method for predicting the quality of ready-mixed concrete by combining mixer power load statistics with production time information. The input features include statistical values derived from power load statistics together with time-related variables. A trained neural network then outputs key fresh concrete quality indices, including slump and slump flow. Using 457 training datasets and 48 evaluation datasets, the model demonstrated high accuracy in predicting fresh concrete quality. For slump, the accuracy exceeded 80% within $\pm 1.0$ cm tolerance, and for slump flow, the accuracy exceeded 90% within $\pm 7.5$ cm tolerance (Hayano and Kudo, 2021). The proposed method provides acceptable predictive performance, particularly for slump estimation, where the achieved tolerance is comparable to or better than the repeatability and reproducibility limits reported in NEN-EN 12350-2:2019 (NEN-EN 12350, 2019a). For slump-flow prediction, the high percentage of

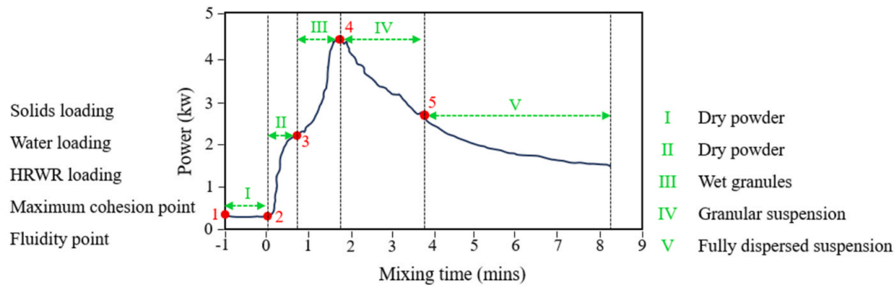


**Fig. 1.** Illustration of mixing power evolution across different mixing stages (Ferraris et al., 2001).

results within ±75 mm indicates suitability for general monitoring; however, the relatively wider tolerance compared with standard test variability (~1.75 times the reported repeatability and reproducibility limits in NEN-EN 12350-8:2019 (NEN-EN 12350, 2019b) suggests that additional validation with tighter error criteria is required for high-precision applications.

### 3.1.2. *Torque and hydraulic pressure*

Mixing power and mixing torque are directly related through equation $P = T\,\omega$, where $P$ is power, $T$ is torque, and $\omega$ the angular speed of the mixer. Rong et al. (2022) measured mixing power by installing a torque sensor and speed control system on a lab-scale twin-shaft mixer, where the torque on the mixing shaft was continuously recorded and converted into power under constant rotational speed. Optimal workability, as indicated by the stabilization of torque, consistently occurred at a characteristic point along the power curve (Rong et al., 2022). An industrial project reported the development of a commercial AI-based system, "Verifi", designed for real-time monitoring of concrete rheology inside mixer truck (Khayat and Libre, 2014). "Verifi" measures concrete slump in transit using an integrated system of sensors and predictive algorithms. Torque sensors in the drum monitor resistance during rotation, while rotational speed and hydraulic pressure help assess mixing power, correlating with slump. These real-time sensor readings are compared with previously calibrated lab-tested slump values using machine learning algorithms, enabling accurate slump estimation during transit. The system continuously tracks changes in concrete consistency and autonomously adjusts water or admixture dosing via automated valves to maintain the target slump before arrival at the job site. An onboard computer manages data processing and control operations, with results transmitted to the cloud portal for full delivery tracking. It eliminates manual slump tests, maintains consistent workability throughout transit, and allows real time adjustments without truck driver intervention and full traceability. Amziane (2005) demonstrated that a concrete mixing truck can be used as a rheometer by monitoring torque during drum rotation at different speeds. The measured torque–speed curve allows the back-calculation of yield stress and plastic viscosity. Field validation showed truck-derived values agreed well with ICAR rheometer, with correlations above 0.9. Hydraulic pressure sensors installed at the inlet and outlet of the drum's hydraulic motor continuously record the pressure required for drum rotation (Jordan et al., 2018). By combining these pressure readings with drum speed data from a speed sensor or accelerometer, the processor calculates the power input per unit time. This resistance to drum rotation serves as an indirect measure of rheology, where higher power consumption demand indicates greater concrete resistance. These signals allow the system to automatically derive slumps, yield stress, and viscosity of fresh concrete.

### 3.1.3. *Summary*

Table 1 summarizes the key characteristics, limitations, and AI integration of in-mixer indirect monitoring methods. Overall, mixing power, torque, and hydraulic pressure offer practical solutions for continuous monitoring by capturing the mechanical response of concrete during mixing or transportation. However, these signals are influenced not only by concrete fresh properties but also by equipment and operational factors, such as mixer geometry, rotational speed, and batch volume. Consequently, correlations established for a specific mixing system may have limited transferability to other equipment or production conditions. This highlights a fundamental trade-off between industrial applicability and measurement generalizability: indirect monitoring methods are readily integrated into production processes but often require system-specific calibration, whereas standardized rheological measurements provide more physically interpretable parameters but are less suitable for continuous monitoring. In this context, AI offers the potential to improve the interpretation of complex sensor signals and establish nonlinear relationships between equipment responses and concrete properties. However, AI does not inherently eliminate equipment dependency, and its generalizability ultimately depends on the diversity and representativeness of the training data.

## 3.2. *Computer vision-based methods*

Computer vision offers a promising solution for monitoring the flow behaviour of fresh concrete by linking visual patterns to flow

**Table 1**
Comparative analysis of in-mixer monitoring methods.

| Criterion | Mixing power (Chopin et al., 2007; Hayano and Kudo, 2021) | Torque (Rong et al., 2022; Amziane, 2005) | Hydraulic pressure (Jordan et al., 2018) | VERIFI system (Khayat and Libre, 2014) |
|---|---|---|---|---|
| Measurement principle | Resistance reflected by power consumption | Resistance reflected by mixing torque | Resistance reflected by hydraulic load/pressure | Torque, rotational speed, and hydraulic pressure measured during drum rotation |
| Relation to fresh properties | Indirect | Indirect | Indirect | Indirect |
| Real-time monitoring | Yes | Yes | Yes | Yes |
| Main limitation | Equipment and operating-condition dependent | Equipment and operating-condition dependent | System-specific calibration | Proprietary system; calibration requirements; |
| AI integration | Yes | No | No | Yes |
| Potential enhancement by AI | / | Time-series prediction and improved interpretation of torque evolution | Nonlinear mapping between pressure signals and workability | / |

characteristics such as plastic viscosity. Images captured during concrete mixing reveal important features, such as surface flow patterns (e.g., smoothness, swirls), motion traits (speed, consistency), texture (gloss, aggregate visibility), and indicators like voids, homogeneity, and bubbles, all closely tied to plastic viscosity during mixing. High-viscosity mixtures show slower, thicker, and more stable flows with distinct surface ridges, while low-viscosity mixtures flow more easily and create smoother surfaces. All these visual patterns are reflected in variations in pixel values within the images, as indicted in Fig. 2. Establishing accurate correlations between visual features and rheological properties remains a significant challenge, as it involves capturing subtle spatiotemporal changes during the mixing process. Deep learning can address this complexity by automatically learning relevant patterns from large image datasets. Convolutional neural networks (CNNs) are commonly used to extract feature maps from an image using a sliding window approach (Guo et al., 2024). The extracted feature map (matrix) serves as the input for training the neural network for classification and regression purpose (Guo et al., 2022). Deep learning can identify subtle relationships between flow behaviour and plastic viscosity.

#### 3.2.1. Image analysis

Juez et al. (2017) developed an inline image analysis method for monitoring concrete mixing. In this study, the image analysis method was based on evaluating the surface texture of the mixture through gray-level histograms. Each captured frame was converted to grayscale, and the standard deviation of pixel intensity distribution (texture index) was calculated to quantify surface roughness and heterogeneity during mixing. The evolution of this texture index over time allowed the identification of key transition points, such as the cohesion point (particles agglomeration) and the fluidity point, providing a robust and non-invasive means of monitoring the mixing process. Ding and An (2017) proposed a real-time method to evaluate the workability (slump flow) of self-compacting concrete during mixing using digital image analysis, which serves as an indicator of concrete quality. An industrial camera was mounted above a single-shaft mixer to capture video frames, where the upper and lower boundaries of concrete lifted by the blades were extracted using image subtraction and watershed segmentation. The vertical distance between these boundaries correlated linearly with slump flow values, enabling indirect workability estimation with less than 5% error in verification. To improve the efficiency of data analysis, Hayano and Kudo (2020) further proposed the deep learning method for directly predicting fresh concrete quality using image data captured near the stirring blades and shaft. The CNN model reached prediction accuracies exceeding 90% for slump and 72% for slump flow. Deep learning–based computer vision enables efficient, non-invasive monitoring of flow behaviour. These advances enable more accurate and automated prediction of fresh concrete flow behaviour through deep learning.

#### 3.2.2. Video analysis

Guo et al. (2022) developed a computer vision video-recognition method for real-time mortar plastic viscosity assessment during mixing, as indicated in Fig. 3. A long-term recurrent convolutional network (LRCN) was applied to capture the dynamic flow behaviour from video frames. This model combines CNN for spatial feature extraction and long short-term memory (LSTM) networks for temporal feature learning, allowing correlation of these features with viscosity values measured by a rheometer. Videos of the mixing process were captured with a cellphone camera (iPhone 12 Pro), and plastic viscosity was measured using an ICAR rheometer. The study defined viscosity ranges from flexural strength data by fitting a curve between plastic viscosity and strength, dividing it into five segments at 21.9, 18.6, 15.3, and 12.0 MPa (15% decrements). The corresponding viscosity ranges were 12–24, 25–34, 35–72, 73–83, and 84–106 Pa s. The proposed method achieved over 99% accuracy in predicting viscosity ranges using the LRCN model, with each assessment taking less than 1 s, enabling near real-time monitoring. Yang et al. (2021) estimated concrete workability by converting mixing videos into over 20,000 labeled image sequences. A CNN–LSTM model extracted spatiotemporal features and predicted slump and slump flow with errors mostly below 10%.

Guo et al. (2026) introduced a non-contact, video-based deep learning approach for real-time prediction of mixing torque, a key indicator of mortar consistency and its evolving rheological behaviour. Instead of relying on specialized torque sensors, the method extracts spatial and temporal information from mixing videos using a hybrid CNN–LSTM framework, in which ResNet-50 captures frame-level features and an LSTM models temporal changes. The model demonstrated high predictive performance, achieving $R^2$ values of 0.992 for training, 0.989 for validation, and 0.936 for testing, with an inference time below 60 ms, enabling real-time application. These results suggest video-based deep learning can replace physical sensors for scalable, cost-effective quality control in concrete and mortar production.

#### 3.2.3. Summary

Table 2 summarizes the characteristics, performance, and limitations of computer vision-based methods. The progression from traditional image analysis to deep learning and video analysis enables automatic extraction of complex spatial and temporal features, reducing reliance on manually defined features. Video-based models are particularly promising because they capture dynamic flow information that cannot be fully represented by individual images. However, performance across studies is not directly comparable, and high dataset-specific accuracy may not translate to reliable performance under different production conditions. Compared with direct property prediction, video-based torque prediction provides continuous, synchronized training data and a physical link between flow behaviour and mechanical resistance. Nevertheless, torque remains an indirect indicator and requires further correlation with specific rheological or workability parameters. The key challenge is therefore to develop robust and transferable models that maintain reliable performance under practical production conditions.

### 3.3. Audio-based method

Sound signals produced during concrete mixing carry useful information that can differentiate between distinct mixing stages. Wilenius et al. (2020) explored the use of audio data and machine learning to monitor the concrete mixing process in real time, aiming to detect different mixing stages and identify potential irregularities. Audio was

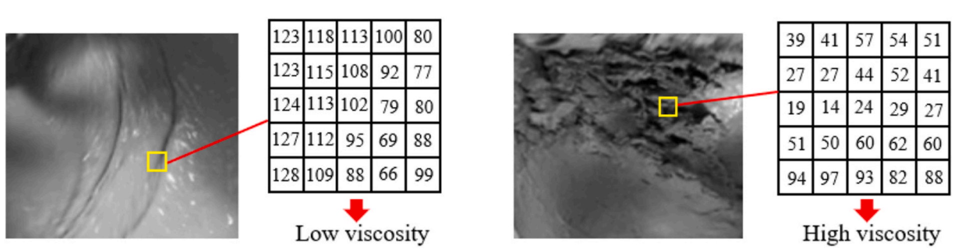


**Fig. 2.** Visualization of pixel intensity variation corresponding to viscosity changes.

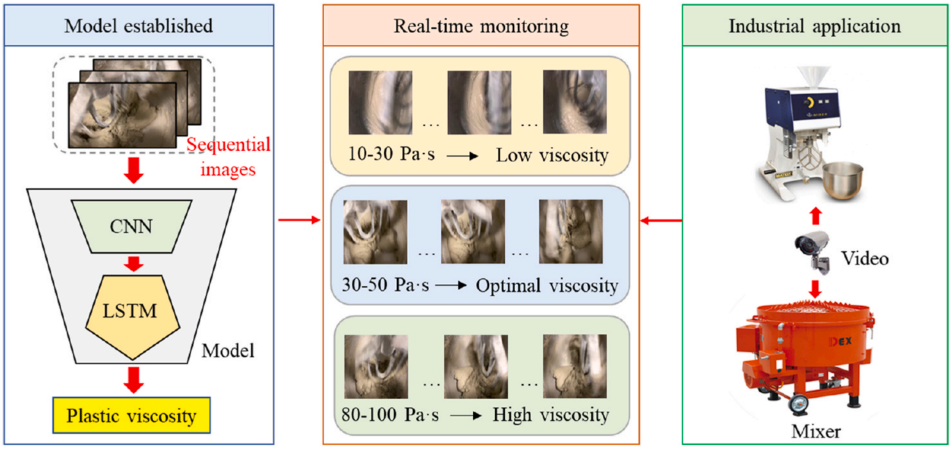


**Fig. 3.** Vision-based real-time monitoring for assessing the rheological properties (Guo et al., 2022).

**Table 2**
Comparison of computer vision-based methods.

| Criterion | Traditional image analysis (Juez et al., 2017; Ding and An, 2017) | CNN-based image analysis (Hayano and Kudo, 2021) | CNN-LSTM (Guo et al., 2022; Yang et al., 2021; Ding and An, 2018) | Video-based torque prediction (Guo et al., 2026) |
|---|---|---|---|---|
| Input data | Individual images | Individual images | Image sequences | Image sequences |
| Feature extraction | Hand-crafted image features | Automatically learned spatial features | Automatically learned spatial and temporal features | Automatically learned spatial and temporal features |
| Target property | Mixing state/slump flow | Slump/slump flow | Plastic viscosity/workability | Mixing torque |
| Temporal information | Limited | Limited | Yes | Yes |
| Real-time potential | Yes | Yes | Yes | Yes |
| Main advantage | Simple and interpretable | Automated feature extraction | Captures dynamic flow behaviour | Enables continuous, synchronized labels for model training |
| Main limitation | Relies on predefined visual features | Limited representation of temporal flow evolution | Data-intensive and dataset-dependent | Data-intensive and dataset-dependent |
| AI integration | No/limited | Yes | Yes | Yes |
| Reported performance | <5% error for slump-flow estimation | >90% accuracy for slump; 72% for slump flow | >99% viscosity-range accuracy; workability errors mostly <10% | Test $R^2 = 0.936$ |

continuously recorded at a concrete factory using a TASCAM DR-05 VoiceTracer, ensuring 48 kHz data can be utilized for study. Audio recordings were collected over a week, resulting in 2100 manually labeled samples belonging to three working conditions: 700 samples for "mixer off", 700 samples for "mixer on without mixing", and 700 samples for "mixer on with mixing", each of the samples is 3 s long. A band-pass filter transformed audio samples into 35-dimensional vectors, which a clustering algorithm grouped into 9 sound patterns representing distinct mixing conditions such as dry mixing, water addition, homogenization, and overmixing. Results indicate that audio analysis can detect irregularities and link sound profiles to concrete quality for improved control and early fault detection. The illustration of proposed method is shown in Fig. 4.

### 3.4. Vibration signal analysis

Vibration data collected from concrete mixers provides a non-invasive means of monitoring mixing quality. Variations in vibration amplitude and acceleration have been shown to correlate with slump, compressive strength, and density (Zhao et al., 2021; Du et al., 2023c). Previous study also demonstrated that characteristic vibration patterns reflect key stages of the concrete mixing process (Wilenius et al., 2020). In this study, a vibration sensor was mounted directly onto a mixer and connected to an on-site data logger, which recorded high-resolution signals at a 96 kHz sampling rate and automatically uploaded the data to a cloud server every minute for one week. These vibration signals were subsequently processed using data-analysis algorithms to infer quality indicators such as mixing uniformity and consistency anomalies.

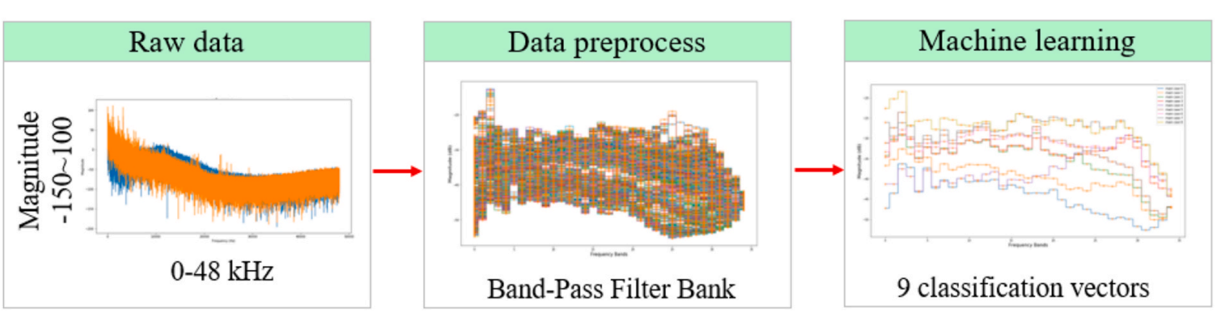


**Fig. 4.** Illustration of audio-based monitoring for identifying concrete mixing stages (Wilenius et al., 2020).

Shifts in vibration frequency, amplitude, or pattern can reveal issues such as poor dispersion, mixing errors, or early mechanical wear that may compromise concrete quality. Because viscosity governs flow behaviour and mixing resistance, changes in vibration response can indirectly reflect variations in viscosity: a stiffer, more viscous mix increases resistance to blade movement and produces higher-intensity vibration signatures, whereas a more fluid mix produces lower vibration levels. Thus, vibration-based monitoring offers valuable indirect insights into the evolving rheological state of the mixture.

Given the complexity of vibration signals, a range of signal-processing techniques can be applied to extract meaningful features before model training. Common approaches include frequency-domain analysis using the Fast Fourier Transform (FFT) (Duhamel and Vetterli, 1990) and statistical feature extraction methods that capture amplitude trends, energy distribution, and transient events. These features can then be organized as time-series inputs for deep learning models. Trained on labeled datasets that incorporate mixing conditions, such models can learn the underlying associations between vibration signatures and flow behaviour. Fig. 5 illustrates how vibration signals can be used to correlate mixing performance with rheological properties.

## 4. Post-mixing monitoring approaches

Section 4 presents post-mixing quality control methods for evaluating flow behaviour. These include image-based feature extraction (Section 4.1), 3D reconstruction approaches (Section 4.2), and accelerometer (Section 4.3)

### 4.1. Image-based methods

#### 4.1.1. Optical flow analysis

A method has been developed by (Coenen et al., 2024) for the automatic evaluation of concrete consistency and rheological properties using image sequences captured during material discharge from a mixing vehicle, as depicted in Fig. 6. Central to this approach is the construction of Spatio-Temporal Flow Fields, a compact two-dimensional representation derived from dense optical-flow computations across video frames, which characterizes the dynamic behaviour of open-channel concrete flow. These flow fields are then fed into a multi-task convolutional neural network (MTCNN), enabling simultaneous regression of slump flow diameter, yield stress, and plastic viscosity, as well as classification of consistency classes. The network was trained and validated on a large real-world dataset comprising nearly 65,000 flow-field samples generated from 18 concrete mixtures. The method achieved high predictive accuracy, with mean errors of approximately 6% for all target properties.

Meyer et al. (2024a) introduced a deep learning approach for time-dependent prediction of fresh concrete properties based on observed flow behaviour. A CNN utilized depth images, optical-flow maps, mix-design parameters, and temporal information to estimate slump flow diameter, yield stress, and plastic viscosity. Depth and optical-flow images were obtained from a binocular camera system during the mixing process, with optical flow computed to quantify pixel-wise motion between consecutive frames. Mix-design parameters included water-to-cement ratio, particle-size distribution, paste content, and admixture dosage, while temporal features represented the elapsed time between the start of mixing and image acquisition. The proposed network achieved mean relative errors of 6.86% for slump flow diameter, 25.30% for yield stress, and 24.23% for plastic viscosity, with respective mean absolute errors of 2.99 cm, 52.05 Pa, and 11.52 Pa s. These results demonstrate that incorporating optical-flow information significantly improves the prediction accuracy for flowability and rheological parameters.

#### 4.1.2. Flow behaviour prediction

Deep learning offers powerful capabilities for both classification and regression, enabling automated prediction of concrete properties such as segregation, flow behaviour, and rheological parameters directly from image data. Idrees et al. (2024) developed a CNN-based VGG-16 model to classify concrete slump values by analyzing video frames captured during discharge from the batching plant hopper. Each video frame is processed using the VGG-16 classifier, and the final slump class is determined through a voting mechanism across all frame-level predictions. This unified approach enables real-time slump estimation directly from chute-discharge videos and achieved an average precision of 85% and an average F1-score of 87% for four slump classes (80 mm, 120 mm, 150 mm, and 180 mm) (Idrees et al., 2024). Akbotina et al. (2025) applied a YOLOv8-based segmentation model to detect segregation in fresh concrete. The model trained on 219 slump flow images labeled as concrete, aggregate segregation, and paste bleeding, reached a segmentation precision of 94.6%. CNNs are also capable of classifying concrete images at different setting stages, allowing the distinction between fresh and hardened material (Wang et al., 2021). When periodic surface images are captured during pouring, such models can detect and quantify defects such as segregation in real time. In this study, a ResNet-50–based monitoring system was trained on 15,000 labeled images categorized as unqualified, medium, or qualified, achieving an average F1-score of 97.97% when validated on a large dam construction site, with performance comparable to expert assessments. Ren et al. (2023) further integrated StyleGAN2 for synthetic data generation, SE-ResNet50 for feature extraction, and a semi-supervised approach, achieving 96% accuracy with only 20% labeled data. These findings demonstrate the potential of deep learning methods for on-site monitoring of fresh concrete.

#### 4.1.3. Flow dimensions quantification

Segregation and bleeding are critical aspects of fresh concrete behaviour, both heavily influenced by its rheological properties. Segregation occurs when yield stress is too low to suspend particles, while plastic viscosity does not affect segregation but determines the speed of reaching a stable state (Yan et al., 2020). Therefore, proper control of rheological parameters is essential to ensure stability in fresh concrete. The flow table test is primarily intended to evaluate the workability of fresh concrete by measuring the spread diameter; however, it does not directly indicate the segregation of the concrete (Roussel, 2007). Schack et al. (2024b) proposed a novel image-based approach that automatically derives multiple fresh concrete properties

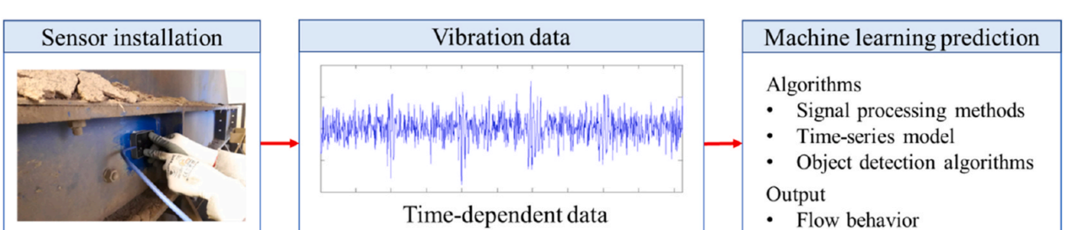


**Fig. 5.** Illustration of vibration-based monitoring for concrete quality control (Wilenius et al., 2020).

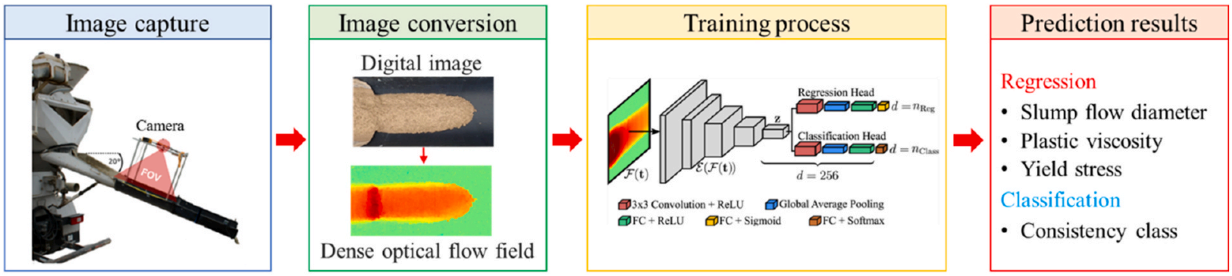


**Fig. 6.** Illustration of deep learning-based monitoring of fresh concrete properties using spatio-temporal flow fields derived from open-channel flow observations (Coenen et al., 2024).

during the flow table test using digital image analysis and deep learning techniques to measure segregation. The proposed method enhances quality control from a single 2D image of the spread concrete surface. The methodology involves capturing digital images after the flow table test, correcting perspective distortion using the known dimensions of the test table, and applying a hierarchical segmentation approach, as shown in Fig. 7. Hierarchical segmentation involves several steps: (1) A region growing (RG) algorithm separates the image into background and other regions; (2) A convex hull algorithm is applied, and the results are compared with those from the RG method to identify the paste separation; (3) U-Net model performs instance segmentation to distinguish aggregate particles from the paste; (4) The suspension region is extracted by removing pixels associated with the background, paste separation, and aggregates from the image. From these segmented regions, key parameters such as flow diameter (consistency), surface paste content, and peripheral paste separation can be calculated at the pixel level (Schack et al., 2024b). The method was validated on more than 1000 images and 200 mixtures.

#### 4.1.4. Summary

Deep-learning-based image analysis has enabled a wide range of techniques for monitoring the flow behaviour of fresh concrete. By extracting visual information from optical flow maps, depth images, RGB images, and full video sequences, these methods can predict rheological parameters, classify workability, and detect defects such as segregation or bleeding. Compared with traditional manual measurements, image-based approaches offer non-contact, automated, and real-time evaluation capabilities that are well suited for on-site quality control. Table 3 provides a consolidated overview of representative deep-learning methods, their input data sources, model architecture, and application objectives.

### 4.2. Three-dimensional reconstruction

#### 4.2.1. Laser depth camera

LiDAR measures distances by calculating the travel time of laser pulses, enabling the creation of detailed 3D maps or surface profiles (Hawley and Gräbe, 2022; Yoon et al., 2026). LiDAR technology can be employed to perform 3D reconstruction of the slump flow profile. Yoon et al. (2023) proposed a framework integrating point cloud analysis from mini-slump tests and a neural network model was proposed to rapidly and accurately characterize rheological properties (yield stress, plastic viscosity) and bleeding of cementitious materials, as shown in Fig. 8. Detailed 3D data of the slump cone was captured using a laser-based depth camera (Intel RealSense L515) and analyzed to extract the corresponding diameter, height, and curvature. The diameter, height, and curvature were used as input variables, while yield stress, plastic viscosity, and bleeding were used as target properties to construct the dataset. This dataset was then used to train a neural network. After training, the model achieved superior predictive accuracy, with an average prediction error of approximately 10.3%, thereby streamlining rheology and bleeding evaluation in cementitious materials for field applications.

Concrete slump flow can also be captured using low-cost depth sensing, enabling full spatiotemporal reconstruction of the spreading concrete surface. Kim and Park (2018) proposed the Kinect-based 4D slump test, which records time-varying depth images of fresh concrete during the slump flow test and processes them through a structured pipeline. After capturing the depth data, the ground plane is first identified through a robust plane-fitting method, followed by a coordinate transformation that converts the point cloud from the camera coordinate system into the slump-test reference frame. At each step, the concrete surface is reconstructed using triangulated irregular network meshing and then resampled through grid interpolation to produce a dense, uniformly spaced height map. Cross-sections extracted sequentially over time are stacked along the temporal axis to form a “4D slump image,” which compresses the entire slump-flow sequence into a single interpretable representation. This visualization enables automatic computation of key workability metrics, including slump-flow diameter, $T_{50}$ time, and height evolution without manual measurement. This low-cost, non-contact method enables repeatable workability assessment and supplies high-resolution data for flow-simulation validation.

#### 4.2.2. 3D scanner

White and Lees (2023) introduced a method to predict fresh concrete's yield stress directly from the height of the unyielded region obtained in a standard slump test, where height was measured using high-resolution structured-light 3D scanning with an Artec Leo handheld scanner. The height of the unyielded region is the vertical distance from the top of the deformed concrete after a slump test down to the point where the material first begins to flow. The workflow for this study is illustrated in Fig. 9. Across 21 tests with slump heights ranging from

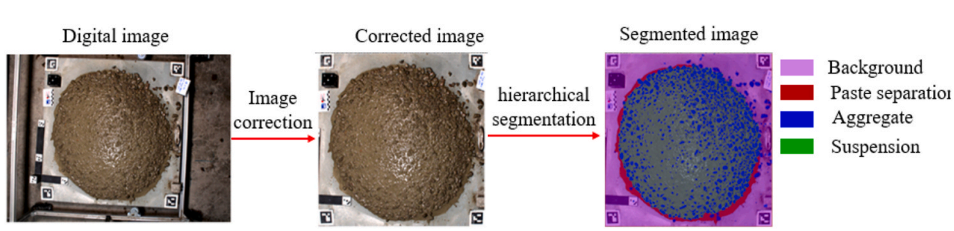


**Fig. 7.** Illustration of image segmentation achieved through a hierarchical segmentation (Schack et al., 2024b).

**Table 3**
Image-based methods for monitoring concrete post-mixing flow behaviour.

| Flow behaviour | Data | Method | Note | Ref. |
|---|---|---|---|---|
| Slump flow diameter; plastic viscosity; yield stress | Optical flow maps | CNN/ transformer | Predict the slump flow diameter, plastic viscosity, and yield stress of concrete discharged from a mixing truck | (Coenen et al., 2023, 2024; Cazacliu and Legrand, 2008) |
| Consistency class | Optical flow maps | CNN/ transformer | Predict the consistency class of fresh concrete | (Coenen et al., 2023, 2024; Cazacliu and Legrand, 2008) |
| Slump flow diameter; plastic viscosity; yield stress | Depth images, optical-flow maps, mix-design parameters, and temporal information | CNN | Predict the slump-flow diameter, plastic viscosity, and yield stress using hybrid data | (Meyer et al., 2024a, 2024b) |
| Slump | Digital images | VGG-16 model | Slump value classification of discharge hopper | Idrees et al. (2024) |
| Segregation and bleeding | Digital images | YOLO-V8 | Using object detection algorithm to detect aggregate segregation and paste bleeding | Akbotina et al. (2025) |
| Setting stage classification | Digital images | ResNet-50 | Classify concrete images at different setting stages to distinguish fresh from hardened material | Wang et al. (2021) |
| Segregation | Digital images | Semi-supervised CNN | Detect segregation or bleeding during pouring; real-time quality assessment using limited labeled data | Ren et al. (2023) |
| Segregation | Digital images | U-Net | Flow diameter measurement based on pixel level segmentation image | Schack et al. (2024b) |
| Slump | Digital images | 3D CNN | Real-time slump classification from chute-discharge videos | Kim et al. (2026) |

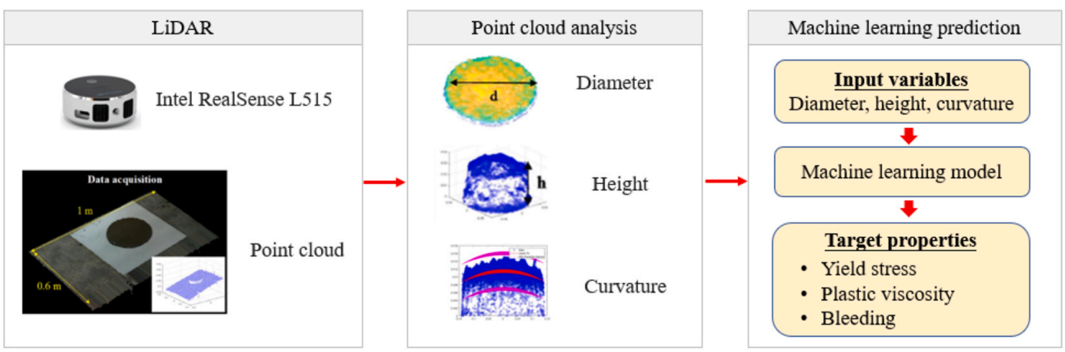


**Fig. 8.** Illustration of assessing fresh properties through point cloud analysis (Yoon et al., 2023).

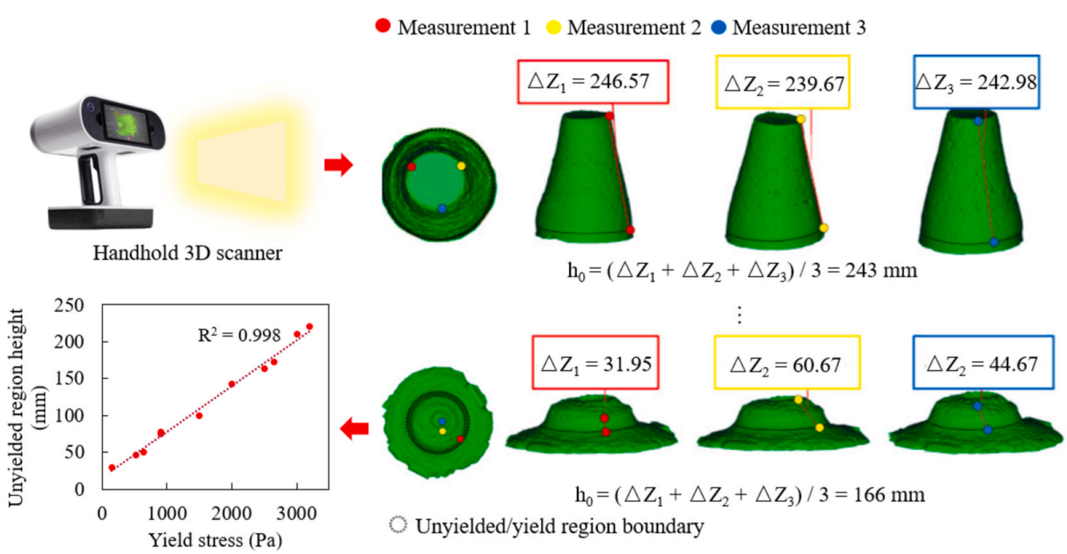


**Fig. 9.** Workflow for determining the unyielded-region height via 3D scanning (White and Lees, 2023).

50 to 240 mm and ICAR-rheometer–measured yield stresses between 127 and 3104 Pa, the 3D-scanned unyielded-region height exhibited a strong linear correlation with yield stress ($R^2 = 0.998$). This corresponds to the von Mises yield criterion, and by using the unyielded-region height in that criterion, the method predicts yield stress with a mean error of just 5% (maximum 10%). This approach enables precise extraction of a key rheological parameter from the slump test for automated on-site measurements. The von Mises yield criterion is expressed as follows:

$$\tau_0 = \frac{\rho g h_0}{\sqrt{3}} \tag{1}$$

where $\rho$ denotes the material density (kg/m$^3$), $g$ is the gravitational acceleration ($\approx$9.81 m/s$^2$), $h_0$ represents the height of the unyielded region (mm); and $\tau_0$ is the yield stress (Pa).

#### 4.2.3. Multi-view stereo

3D reconstruction of the slump cake can also be achieved with multi-view stereo, generating a 3D surface model from multiple images, as illustrated in Fig. 10 (Schack et al., 2024a). Through bundle adjustment and dense stereo matching, a detailed 3D point cloud is created using Agisoft Metashape, incorporating Structure-from-Motion techniques. The heterogeneous texture of fresh concrete, resulting from variations in aggregate size, facilitates accurate reconstruction. Although reflective wet areas may cause localized data loss, these gaps are mitigated through interpolation during mesh generation. The resulting 3D model captures critical geometric characteristics of the slump cake. The height distribution of various elements in the 3D model can be represented by a frequency density function. Notably, particle agglomeration in the central region leads to a discontinuous surface profile, observable in the height distribution of the 3D model. Tuan et al. (2021) developed a custom stereo camera and Mask R-CNN classified slump types ("True," "Shear," "Collapse") with over 93.5% accuracy and computed slump depth and volume with less than 2.05% error in outdoor settings.

#### 4.2.4. Summary

Table 4 compares the main 3D reconstruction methods for fresh concrete assessment. Laser depth cameras enable rapid and relatively low-cost 3D data acquisition but are limited by sensing range, depth resolution, calibration requirements, and sensitivity to ambient light and reflective surfaces. High-resolution 3D scanners provide more accurate geometric measurements and physically interpretable rheological estimation, although their higher cost and scanning requirements may restrict practical deployment. Multi-view stereo offers a flexible camera-based alternative but requires sufficient image quality and viewpoint overlap, while occlusion, reflective surfaces, and poor texture can lead to incomplete reconstruction. Its multi-stage reconstruction process is also computationally demanding and susceptible to accumulated errors in camera pose estimation and feature matching. Overall, these methods improve the objectivity and information content of conventional fresh concrete tests, while AI can further link complex 3D features to rheological properties. However, their sensitivity to sensing conditions and their reliance on post-mixing tests remain major barriers to robust, continuous in-process monitoring.

### 4.3. Accelerometer

An accelerometer offers a promising tool for measuring rheological properties. The traditional slump test is transformed into a rheology test by combining it with a wireless accelerometer to capture slump cessation time, enabling on-site quantification of plastic viscosity (White and Lees, 2025). Twenty-four concrete mixes were tested, with yield stress ranging from 318 to 3268 Pa, viscosity from 1.9 to 17.5 Pa s, and slump from 44 to 240 mm. Dimensional analysis then links the measured cessation time and associated variables to rheological parameters via semi-empirical formulae, as summarized in Eq. (2):

$$\mu = \frac{\tau_0 T_S}{300} \tag{2}$$

where $\tau_0$ is the yield stress (Pa); $T_S$ denotes the slump cessation time (s); and $\mu$ represents plastic viscosity (Pa.s). In this study, $\tau_0$ is determined using the method described in Section 3.2.5.2.

An x-IMU3 inertial measurement unit (Bluetooth-enabled, 400 Hz) was placed on the concrete in every slump test to precisely mark when flow began and ended. Measured slump cessation times ranged from 0.5 to 2.5 s, with an average of 1.5 s. Yield stress was obtained from the 3D-scanned unyielded-region height (Section 3.2.6.2). The viscosity was calculated from the accelerometer-derived slump time and yield stress using Eq. (2). The result matched rheometer measurements within about 10% (±0.6 Pa s). The general workflow for measuring slump cessation time is shown in Fig. 11.

## 5. Strengths and challenges

This section discusses different techniques, compares their strengths, identifies current challenges, and outlines future perspectives. Section 5.1 summarizes the application domains of each technique, Section 5.2 reviews their technology readiness levels, and Section 5.3 highlights the strengths of AI in data analysis. Section 5.4 identifies key challenges in existing studies, while Section 5.5 proposes future research directions.

### 5.1. Application domains

Table 5 summarizes different indirect methods for monitoring flow behaviour, such as rheological parameters, flowability, segregation, and bleeding. In the concrete domain, vision-based sensing (image, video, and optical flow) has been used to evaluate flowability and rheological properties, while audio data, ultrasonic sensors, vibration sensors, mixing power, torque, hydraulic pressure, accelerometers, and 3D reconstruction techniques (depth camera, 3D scanning, multi-view stereo) have been used to monitor mixing conditions, flow behaviour, rheological properties, and segregation.

### 5.2. Technology readiness level

The technology readiness levels (TRLs) indicate the maturity of methods used for quality assessment of the concrete. As recommended by the Dutch Research Council, TRLs serve as a key metric for selecting appropriate techniques. The scale ranges from 1 to 9, where TRL 1

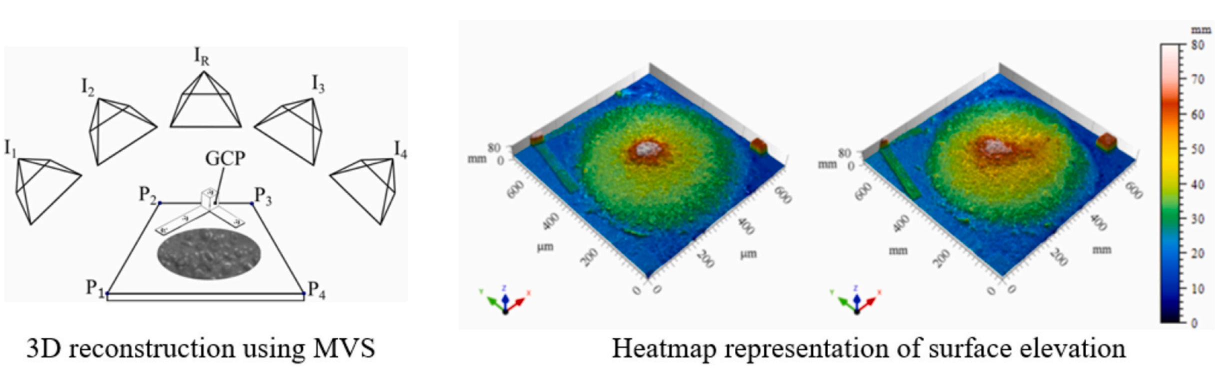


**Fig. 10.** 3D surface model of a concrete slump test generated by multi-view stereo (Schack et al., 2024a).

**Table 4**
Comparison of 3D reconstruction methods.

| Criterion | Laser depth camera (Yoon et al., 2023; Kim and Park, 2018) | 3D scanner (White and Lees, 2023) | Multi-view stereo (Schack et al., 2024a) |
|---|---|---|---|
| Data acquisition | Laser/depth sensing | Structured-light scanning | Multiple RGB/stereo images |
| Output | Point cloud | Point cloud | Point cloud |
| Target properties | Rheology, bleeding, workability | Yield stress | Slump type, depth, volume |
| Real-time potential | High | Limited | Limited |
| Main advantage | Low-cost implementation | High geometric accuracy | Low-cost implementation |
| Main limitation | Limited range/resolution; sensitive to ambient light, reflective surfaces, motion, and calibration | Higher equipment cost and scanning requirements | Sensitive to image quality, texture, reflection, occlusion, and viewpoint overlap; computationally demanding |
| AI integration | Yes | No/limited | Yes |

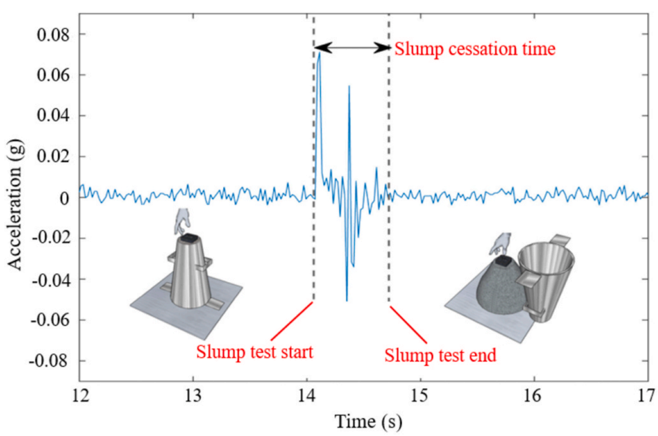


**Fig. 11.** Illustration of slump cessation time determined by accelerometer measurements (White and Lees, 2025).

represents basic principles observed and TRL 9 represents technologies that have been fully developed and validated for practical application, as shown in Fig. 12 and aligned with reference (Manning, 2023).

Table 6 summarizes the advantages and limitations of existing methods and indirect measurement techniques based on TRLs, measurement time, accuracy, impact on mixing, automation potential, and suitability for on-site use. The TRL assigned to each technology was qualitatively assessed based on the maturity of its reported development and practical deployment described in the reviewed literature. Specifically, the assessment considered whether the technology had progressed from laboratory proof-of-concept to validation in relevant environments, prototype demonstration, or routine implementation in industrial or field applications, following the TRL definitions shown in Fig. 12. Since this review synthesizes published studies rather than performing independent technology validation, the assigned TRLs represent the authors' qualitative assessment of the current state of the literature. The comparison in Table 6 highlights the trade-offs between traditional and emerging methods for measuring concrete fresh behaviour. Rheometers, at TRL 9, remain the benchmark for precision in measuring rheological properties but are costly and time-consuming (5–30 min). Mixing resistance methods such as mixing power, torque, and hydraulic pressure sensing are also at TRL 9, offering practical and reliable on-site monitoring. In contrast, indirect methods like image analysis and video analysis are fast (under 1 s), non-invasive, and inexpensive, making them suitable for real-time field applications, though with varying accuracy. Techniques like 3D reconstruction show

**Table 5**
Summary of flow behaviour monitoring methods.

| No. | Methods | | Application | Stage | Target properties | Ref. |
|---|---|---|---|---|---|---|
| 1 | Computer vision | Image-analysis | Concrete | During mixing | Mixing condition, slump, slump flow | (Hayano and Kudo, 2021; Juez et al., 2017; Ding and An, 2017) |
| 2 | | Video-analysis | Mortar/ Concrete | During mixing | Plastic viscosity, slump, slump flow | (Guo et al., 2022, 2026) |
| 3 | | Optical flow | Concrete | Post-mixing | Plastic viscosity, yield stress, slump, slump flow | (Coenen et al., 2024; Meyer et al., 2024a) |
| 4 | | Image segmentation | Concrete | Post-mixing | Segregation | (Schack et al., 2024b; Akbotina et al., 2025) |
| 5 | | Image-classification | Concrete | Post-mixing | Slump, segregation | (Idrees et al., 2024; Wang et al., 2021) |
| 6 | Acoustic | Audio data | Concrete | During mixing | Mixing condition | Wilenius et al. (2020) |
| 7 | Mixing resistance | Mixing power | Concrete | During mixing | Mixing condition, slump, slump flow, plastic viscosity, yield stress | (Cazacliu and Roquet, 2009; Hayano and Kudo, 2021) |
| 8 | | Mixing torque/Hydraulic pressure | Concrete | During mixing | Mixing condition, slump, plastic viscosity, yield stress | (Amziane, 2005; Jordan et al., 2018) |
| 9 | 3D reconstruction | Depth camera | Concrete | Post-mixing | Plastic viscosity, yield stress, bleeding | Yoon et al. (2023) |
| 10 | | 3D scanner | Concrete | Post-mixing | Segregation, bleeding | White and Lees (2023) |
| 11 | | Multi-view stereo | Concrete | Post-mixing | Yield stress | (Schack et al., 2024a; Tuan et al., 2021) |
| 12 | - | Accelerometer | Concrete | Post-mixing | Plastic viscosity | White and Lees (2025) |
| 13 | - | Vibration sensor | Concrete | During mixing | Mixing condition | Wilenius et al. (2020) |

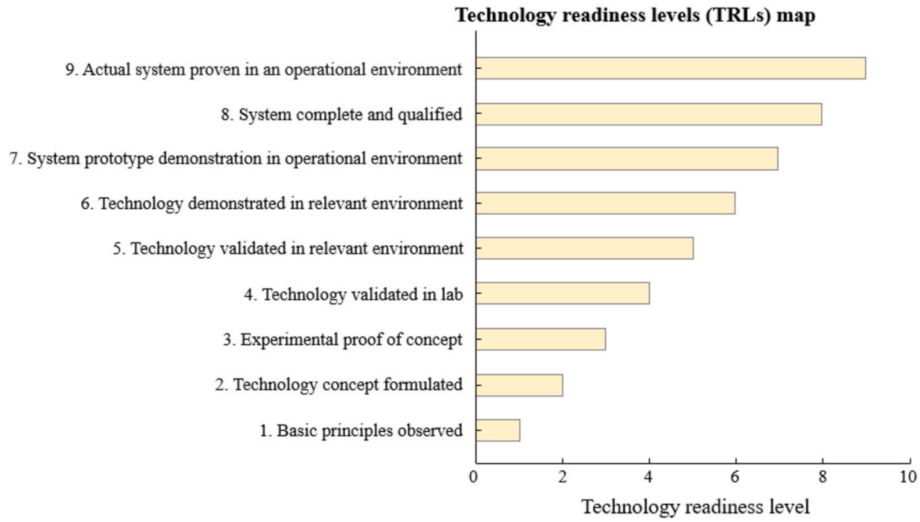


**Fig. 12.** TRLs as defined by the Dutch Research Council (Manning, 2023).

**Table 6**
Summary of the reviewed technologies for concrete quality assessment.

| Methods | TRLs | Cost | Data format | Time | Accuracy | Mixing disturbance | Field use | Ref. |
|---|---|---|---|---|---|---|---|---|
| Rheometer | 9 | High | Time-dependent data | 15-30 min | High | Yes | Yes/ No | (Du et al., 2023a; Khayat et al., 2019; Du et al., 2023b; BTRHEOM, 2004) |
| Workability test | 9 | Low | - | Few minutes | Low to high | Yes | Yes | (Fares, 2015; Meng and Khayat, 2017b; Girish et al., 2010) |
| Mixing resistance methods (Torque, power, pressure) | 8-9 | Low | Time-dependent data | < 1 s | High | No | Yes | (Cazacliu and Roquet, 2009; Chopin et al., 2007) |
| Image analysis | 5-7 | Low | 2D image | < 1 s | High | No | Yes | (Coenen et al., 2024; Wang et al., 2021; Ren et al., 2023) |
| Optical flow | 5–6 | Low | Sequential images | < 1 s | High | Yes | Yes | (Coenen et al., 2024; Meyer et al., 2024a) |
| Video analysis | 4–6 | Low | Sequential images | < 1 s | High | No | Yes | (Guo et al., 2022; Ngo et al., 2016; Yang et al., 2021) |
| Image segmentation | 4–6 | Low | 2D image | < 1 s | High | Yes | Yes | (Schack et al., 2024b; Akbotina et al., 2025) |
| Depth camera | 4–6 | Low | Point cloud | Few minutes | High | Yes | Yes | Yoon et al. (2023) |
| Multi-view reconstruction | 4–6 | Low | Multi-view 2D images | 5 min | High | Yes | Yes | (Schack et al., 2024a; Tuan et al., 2021) |
| 3D scanner | 4–6 | High | Point clouds | 5–10 min | High | Yes | Yes | White and Lees (2023) |
| Accelerometer | 2–4 | Low | Time-dependent data | 2-3 min | High | Yes | Yes | White and Lees (2025) |
| Audio analysis | 2–3 | Low | Time-dependent data | Few seconds | Low | No | Yes | Wilenius et al. (2020) |
| Vibration sensor | 2–3 | Low | Time-dependent data | Few seconds | Low | No | Yes | Wilenius et al. (2020) |

promise for assessing agglomeration and segregation but remain at lower TRLs. Acoustic, audio, and vibration sensors provide quick, low-cost insights into mixing stages, with minimal disturbance but lower accuracy.

### 5.3. AI-assisted evaluation

This section presents AI models tailored to data from each technique. For time-dependent inputs such as audio, vibration, power, or torque signals, time-series models like recurrent neural networks (RNNs) are typically employed for prediction and classification. The target properties can be mixing condition, rheology, and workability. In the case of time-sequential visual data like video, a combination of CNNs and RNNs (e.g., LSTM) is effective. This approach allows CNNs to extract spatial features from each frame while RNNs capture temporal patterns across frames. For image-based classification tasks, such as evaluating the surface quality of concrete, CNNs are used to extract feature maps from images. The CNN + LSTM can be used to predict rheology and workability. Object detection algorithms can also be used to identify peak values in time-dependent sensor data and spectroscopy data, which is useful for highlighting critical events or changes. Furthermore, 3D reconstruction methods (e.g., 3D scanner and multi-view stereo) can be applied to generate three-dimensional surface models of concrete, enabling precise quantification of surface irregularities or defects. To note, the instance segmentation is a critical method to evaluate the shape, size, and consistency of the concrete mixture based 2D image data. Also, the instance segmentation can be combined with multi-view stereo 3D reconstruction (Deng et al., 2023). The summary of the AI-powered assessment of flow behaviour is shown in Table 7.

AI can improve the interpretation of complex sensing data and capture nonlinear relationships with fresh concrete properties, but it does not inherently eliminate limitations in data acquisition. Poor image quality, sensor noise, equipment dependency, and environmental interference can still propagate into model predictions. Therefore, advances in AI should be accompanied by improvements in sensing reliability and data quality rather than being considered a substitute for

**Table 7**
Summary of AI-powered concrete quality assessment.

| Methods | Model | Data format | Objective | Target properties |
|---|---|---|---|---|
| Machine learning | ANN, SVM, Random Forest | Time-dependent data | Correlate viscosity with other sensors | Yield stress, plastic viscosity, slump, slump flow |
| CNN | ResNet, VGG, DenseNet | 2D image | Classify the images | Mixing condition, slump, slump flow |
| RNN | LSTM | Time-dependent data | Process the time-dependent data for prediction | Mixing condition, yield stress, plastic viscosity, slump, slump flow |
| CNN + LSTM | LRCN | Video data | Process the video/sequential images for prediction | Plastic viscosity; slump. Slump flow |
| Object detection | Faster-RCNN, YOLOv8 | 1D spectra, time-dependent data | Select peak value from the Time-dependent data | Peak value for spectra data |
| Instance segmentation | Mask-RCNN, UNet, DeepLab | 2D image | Pixel-wise classification labels each pixel, enabling measurement of shape and size. | Segregation, bleeding |

robust measurement.

### 5.4. Limitation in existing studies

Based on the above TRL investigation, one key challenge is identified: Some techniques have only been validated in laboratory settings (e.g., vision-based methods), and their effectiveness in real-world on-site applications remains uncertain. In laboratory settings, lighting is uniform, surfaces are clean, and environmental disturbances (e.g., variable daylight, surface soiling) are minimal. On a real-world construction site, however, factors like variable daylight, surface soiling, ambient noise and vibration, and fluctuating temperatures can degrade sensor accuracy and algorithm performance. Consequently, further experiments in complex, real-world environments are needed to uncover and address challenges and ultimately realize full automation. Many existing studies rely on relatively small datasets collected under controlled experimental conditions. These datasets often lack diversity in terms of concrete designs, aggregate types, environmental conditions, and construction scenarios. As a result, the generalizability of the proposed models and algorithms remains uncertain when applied to different construction sites or varying operational conditions. For computer vision-based methods, most studies focus on the post-mixing stage, assessing concrete quality during discharge, after the slump test, or once casting is complete. But this has several challenges: (1) Measuring rheological properties during the discharge stage is relatively late, limiting opportunities for early adjustments and proactive quality control. If concrete fails quality check during discharge, it may need to be discarded or reprocessed. (2) Measuring the quality of concrete after casting is often too late, as it leaves no room for corrective action. By this stage, the concrete has already begun setting, and any issues such as poor workability, segregation, or inconsistent mix proportions can compromise structural performance and durability. (3) Conventional slump or slump-flow tests require manual sampling and off-line measurements, making them time-consuming and labor-intensive. Because the tests provide only discrete measurements, they cannot continuously monitor changes in fresh concrete workability during mixing or provide real-time feedback for process control.

### 5.5. Future perspectives

#### 5.5.1. Multi-sensor collaboration

Indirect measurement of fresh concrete properties based on a single sensing modality is often prone to error. For example, torque sensors record only local resistance changes during mixing and may fail to capture the overall rheological state of the batch, whereas image-based methods capture the overall mixing state but generally lack the accuracy needed for precise quantification. To address these limitations, future research should explore multi-sensor frameworks that fuse temporal signals, such as torque, with spatial data from images or video. By combining the evolving resistance profiles revealed by time-series sensors with the dispersion, agglomeration, and surface anomaly information extracted from visual inputs, a collaborative model can generate more accurate and robust property predictions. Recent research has demonstrated the potential of multimodal sensing for monitoring concrete mixing. For example, Sheng et al. (2026) integrated computer vision, dynamic torque sensing, and thermal profiling to monitor the mixing process of 3D-printable concrete. Fusing heterogeneous data streams requires careful synchronization of sampling rates and the implementation of robust preprocessing pipelines to mitigate noise and environmental variability. Recent developments in attention-based neural architecture and graph-based learning offer promising strategies for fusing heterogeneous sensor signals into a unified predictive model (Kovalenko et al., 2024). Integrated multi-sensor systems have the potential to improve the reliability of real-time concrete workability monitoring. However, practical deployment will require robust sensor calibration, synchronization, and validation under industrial production conditions.

#### 5.5.2. Advanced large-scale language models

Recent advances in visual language models (VLMs), which integrate image understanding with natural language reasoning, offer promising opportunities for explaining and monitoring the concrete mixing process and quality control (Che et al., 2023). By processing visual data such as videos captured during mixing, VLMs can interpret key phenomena, including material dispersion, agglomeration, wetting stages, and the onset of homogenization. In addition to visual interpretation, the models can generate descriptive language outputs, providing real-time, human-readable explanations of the material behaviour at various stages. This capability enables automated assessment of mixing quality, early detection of anomalies (e.g., bleeding, inadequate wetting, fiber clustering), and documentation of the mixing process without relying solely on sensor-based measurements. Integrating VLMs into concrete production could significantly enhance process transparency, quality control, and decision-making in complex, dynamic mixing environments. The inputs for VLMs can include concrete quality images, slump flow test images, and construction site photos, as well as videos capturing the mixing process or casting sequences. Each image or video-based sample should be paired with corresponding textual data, such as descriptions like "good mixing", "segregation observed", or specific task instructions.

Large language models (LLMs) represent another category of multimodal models, with their advanced capabilities in understanding, generating, and reasoning over complex textual information (Kasneci et al., 2023), present new opportunities for enhancing the explanation and monitoring of the concrete mixing process. By analyzing structured data (e.g., sensor outputs, mixing parameters) and unstructured data (e.g., technician notes, visual observations converted to text), LLMs can interpret the evolving state of the mixture, identify potential issues such as inadequate dispersion or overmixing, and generate real-time diagnostic reports. Additionally, LLMs can assist in translating low-level sensor readings into high-level, human-readable insights, facilitating better decision-making and quality control. Their ability to integrate multiple data sources and provide contextualized reasoning makes LLMs a powerful tool for advancing automation and transparency in concrete production workflows. Future research should therefore focus on developing trustworthy and deployable AI systems rather than relying solely on increasingly powerful models.

While advances in sensing technologies, increased data availability, and more capable AI methods have the potential to significantly improve monitoring, prediction, and decision support, they should not be viewed as a standalone solution to the challenges discussed in this article. Simply increasing the number of sensors, the amount of data, or the complexity of AI models does not necessarily lead to better outcomes. Their effectiveness depends on factors such as data quality and representativeness, appropriate system design, integration of domain knowledge, and human expertise in interpreting and acting upon the results. Therefore, these technologies should be regarded as important enablers within a broader decision-making framework rather than as a complete solution.

## 6. Conclusion

This review analyzes recent advances in AI-powered real-time indirect methods for assessing the flow behaviour of fresh concrete, primarily focusing on the in-process mixing and post-mixing stages. It systematically examines a wide range of computer vision and sensing techniques, their underlying principles, performance, TRLs, and the potential of AI integration to enhance automation, accuracy, and real-time applicability in field conditions. We can draw the following conclusions.

- Advanced sensing and vision-based techniques, including computer vision, vibration, sound, LiDAR, 3D scanning, accelerometers, torque sensing, and power consumption analysis, provide faster, non-invasive, and field-adaptable alternatives to traditional rheometers and conventional field tests, although many of these technologies remain at relatively early technology readiness levels.
- The integration of artificial intelligence, including machine learning and deep learning techniques, greatly enhances the capability to extract meaningful features from complex sensor data, enabling more accurate prediction of rheological properties and related behaviours. AI-driven analysis also facilitates real-time monitoring, anomaly detection, and data-driven decision-making during concrete production and placement.
- Multi-sensor data acquisition and automated analysis frameworks are essential for overcoming the limitations of single-sensor approaches. The fusion of heterogeneous data sources, such as visual, acoustic, mechanical, and geometric information, can improve robustness and reliability under variable field conditions, including changing illumination, noise, vibration, and environmental disturbances.

Future research should emphasize large-scale field validation, standardized evaluation protocols, and the development of robust multimodal data fusion frameworks. In addition, emerging technologies such as large language models and AI-assisted decision-support systems have the potential to further enhance transparency, interpretability, and automation in concrete quality monitoring, ultimately enabling intelligent and fully integrated concrete quality management throughout the construction lifecycle.

## CRediT authorship contribution statement

**Pengwei Guo:** Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft. **Le Teng:** Writing – review & editing. **Neil Yorke-Smith:** Supervision, Writing – review & editing. **Sandra Barbosa Nunes:** Conceptualization, Project administration, Resources, Writing – review & editing.

## Declaration of competing interests

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

## Acknowledgement

The authors thank the anonymous reviewers for their suggestions. This research was not supported by any specific funding.

## Data availability

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

## References

Abrishambaf, A., Pimentel, M., Nunes, S., Costa, C., 2022. Multi-level study on UHPFRC incorporating ECat. Constr. Build. Mater. 318, 125976.
Akbotina, A., Chung, S.-Y., Sikora, P., 2025. Deep learning-based image analysis for confirming segregation in fresh self-consolidating concrete. Appl. Rheol. 35 (1), 20250038.
Amziane, S., 2005. Measurement of workability of fresh concrete using. J. Res. Nat. Inst. Stand. Technol. 110 (1–3), 55.
Benaicha, M., Jalbaud, O., Burtschell, Y., 2025. Investigating stability, homogeneity, and bleeding in self-compacting concrete: new experimental analysis. Euro. J. Environ. Civil Eng. Des. 29 (5), 901–915.
BTRHEOM. URL: http://www.pontiestrade.com/strumenti/btrheom.php.
Bui, V.K., Montgomery, D., Hinczak, I., Turner, K., 2002. Rapid testing method for segregation resistance of self-compacting concrete. Cement Concr. Res. 32 (9), 1489–1496.
Cazacliu, B., Legrand, J., 2008. Characterization of the granular-to-fluid state process during mixing by power evolution in a planetary concrete mixer. Chem. Eng. Sci. 63 (18), 4617–4630.
Cazacliu, B., Roquet, N., 2009. Concrete mixing kinetics by means of power measurement. Cement Concr. Res. 39 (3), 182–194.
Çelik, F., Colak, A.B., Yıldız, O., Bozkır, S.M., 2022. An experimental investigation on workability and bleeding features. ACI Mater. J. 119 (5), 63–75.
Che, C., Lin, Q., Zhao, X., Huang, J., Yu, L., 2023. Enhancing multimodal understanding with CLIP-based image-to-text transformation. In: Proceedings of the 2023 6th International Conference on Big Data Technologies, pp. 414–418.
Chopin, D., Cazacliu, B., Larrard, F.d., Schell, R.d., 2007. Monitoring of concrete homogenisation with the power consumption curve. Mater. Struct. 40 (9), 897–907.
Coenen, M., Vogel, C., Schack, T., Haist, M., 2023. Concrete flow transformer: predicting fresh concrete properties from concrete flow using vision transformers. In: Proceedings of European Conference on Computing in Construction, vol. 4.
Coenen, M., Vogel, C., Schack, T., Haist, M., 2024. Deep concrete flow: deep learning based characterisation of fresh concrete properties from open-channel flow using spatio-temporal flow fields. Constr. Build. Mater. 411, 134809.
Deng, L., Sun, T., Yang, L., Cao, R., 2023. Binocular video-based 3D reconstruction and length quantification of cracks in concrete structures. Autom. ConStruct. 148, 104743.
Ding, Z., An, X., 2017. A method for real-time moisture estimation based on self-compacting concrete workability detected during the mixing process. Constr. Build. Mater. 139, 123–131.
Ding, Z., An, X., 2018. Deep learning approach for estimating workability of self-compacting concrete from mixing image sequences. Adv. Mater. Sci. Eng. 2018 (1), 6387930.
Du, J., Guo, P., Liu, Z., Meng, W., 2023a. Highly thixotropic ultra-high-performance concrete (UHPC) as an overlay. Constr. Build. Mater. 366, 130130.
Du, J., Guo, P., Meng, W., 2023b. Effect of water-based nanoclay and ambient temperature on rheological properties of UHPC pastes. Constr. Build. Mater. 370, 130733.
Du, J., Mahjoubi, S., Bao, Y., Banthia, N., Meng, W., 2023c. Modeling mixing kinetics for large-scale production of ultra-high-performance concrete: effects of temperature, volume, and mixing method. Constr. Build. Mater. 397, 132439.
Duhamel, P., Vetterli, M., 1990. Fast fourier transforms: a tutorial review and a state of the art. Signal Process. 19 (4), 259–299.
EN 12350-2: Testing Fresh Concrete - Part 2: Slump Test, 2019.
EN 12350-8: Testing of Concrete Mix - Part 8: Self-Compacting Concrete - Flow Rate, 2019.
Fares, G., 2015. Effect of slump cone orientation on the slump flow time (T50) and stability of sustainable self-compacting concrete containing limestone filler. Constr. Build. Mater. 77, 145–153.
Ferraris, C., De Larrard, F., Martys, N., 2001. Fresh concrete rheology: recent developments. Mater. Sci. Concrete VI 735, 215–241. URL: https://tsapps.nist.gov/publication/get_pdf.cfm?pub_id=860202.
Feys, D., De Schutter, G., Fataei, S., Martys, N.S., Mechtcherine, V., 2022. Pumping of concrete: understanding a common placement method with lots of challenges. Cement Concr. Res. 154, 106720.

Feys, D., Khayat, K.H., 2013. Comparing rheological properties of SCC obtained with the ConTec and ICAR rheometers. In: Proceedings of the 5th North-American Conference on self-consolidating Concrete.
Girish, S., Ranganath, R., Vengala, J., 2010. Influence of powder and paste on flow properties of SCC. Constr. Build. Mater. 24 (12), 2481–2488.
Guo, P., Du, J., Bao, Y., Meng, W., 2022. Real-time video recognition for assessing plastic viscosity of ultra-high-performance concrete (UHPC). Measurement, 110809.
Guo, P., Meng, W., Bao, Y., 2024. Intelligent characterization of complex cracks in strain-hardening cementitious composites based on generative computer vision. Constr. Build. Mater. 411, 134812.
Guo, P., Wagemakers, N., Sandra, N., Yorke-Smith, N., Virginie, W., 2026. Real-Time Prediction of Mixing Torque Using Deep Learning. Rilem 2026 Spring Convention.
Hawley, C.J., Gräbe, P., 2022. Water leakage mapping in concrete railway tunnels using LiDAR generated point clouds. Constr. Build. Mater. 361, 129644.
Hayano, H., Kudo, M., 2020. JP2020144133A: Method for Predicting Quality of Ready-Mixed Concrete. Japan Patent.
Hayano, H., Kudo, M., 2021. JP2021124304A: Quality Prediction Method for ready-mixed Concrete. Japan Patent.
Idrees, S., Nugraha, J.A., Tahir, S., Choi, K., Choi, J., Ryu, D.-H., Kim, J.-H., 2024. Automatic concrete slump prediction of concrete batching plant by deep learning. Dev. Built Environ. 18, 100474.
Jarny, S., Roussel, N., Le Roy, R., Coussot, P., 2008. Thixotropic behavior of fresh cement pastes from inclined plane flow measurements. Appl. Rheol. 18 (1), pp. 14251–1-14251-8.
Jordan, R.K., Roberts, M.F., Glina, Y., Tregger, N.A., Roberts, L.R., Koehler, E.P., 2018. Dynamic Segregation Monitoring of Concrete. US Patents.
Juez, J.M., Artoni, R., Cazacliu, B., 2017. Monitoring of concrete mixing evolution using image analysis. Powder Technol. 305, 477–487.
Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., 2023. ChatGPT for good? On opportunities and challenges of large language models for education. Learn. Indiv Differ 103, 102274.
Khayat, K.H., Libre, N.A., 2014. Automated Measurement and Control of Concrete Properties in a Ready Mix Truck with VERIFI.
Khayat, K.H., Meng, W., Vallurupalli, K., Teng, L., 2019. Rheological properties of ultra-high-performance concrete—An overview. Cement Concr. Res. 124, 105828.
Kim, J.-H., Park, M., 2018. Visualization of concrete slump flow using the kinect sensor. Sensors 18 (3), 771.
Kim, Y., Oh, G., Youm, K., Yu, Y., 2026. AI-powered real-time system for automated concrete slump prediction via video analysis. Autom. ConStruct. 182, 106777.
Kovalenko, A., Pozdnyakov, V., Makarov, I., 2024. Graph neural networks with trainable adjacency matrices for fault diagnosis on multivariate sensor data. IEEE Access 12, 152860–152872.
Liu, Y., Lu, C., Hu, X., Shi, C., 2023. Effect of silica fume on rheology of slag-fly ash-silica fume-based geopolymer pastes with different activators. Cement Concr. Res. 174, 107336.
Lomboy, G.R., Wang, X., Wang, K., 2014. Rheological behavior and formwork pressure of SCC, SFSCC, and NC mixtures. Cement Concr. Compos. 54, 110–116.
Mandal, R., Panda, S.K., Nayak, S., 2023. Rheology of concrete: Critical review, recent advancements, and future prospectives. Constr. Build. Mater. 392, 132007.
Manning, C.G., 2023. Technology readiness levels. URL: https://www.nasa.gov/directorates/somd/space-communications-navigation-program/technology-readiness-levels.
Meng, W., Khayat, K., 2017a. Effects of saturated lightweight sand content on key characteristics of ultra-high-performance concrete. Cement Concr. Res. 101, 46–54.
Meng, W., Khayat, K.H., 2017b. Improving flexural performance of ultra-high-performance concrete by rheology control of suspending mortar. Compos. B Eng. 117, 26–34.
Meyer, M., Langer, A., Mehltretter, M., Beyer, D., Coenen, M., Schack, T., Haist, M., Heipke, C., 2024a. Image-based deep learning for the time-dependent prediction of fresh concrete properties. ArXiv preprint arXiv:.06611.
Meyer, M., Langer, A., Mehltretter, M., Beyer, D., Coenen, M., Schack, T., Haist, M., Heipke, C., 2024b. Fresh concrete properties from stereoscopic image sequences. PFG–J. Photogram., Rem. Sens. Geoinform. Sci. 92 (5), 517–529.
NEN-EN 12350-8: Testing Fresh Concrete - Part 8: Self-Compacting Concrete - Slump-Flow Test *Netherlands Standardization Institute*, 2019.
NEN-EN 12350-2: Testing Fresh Concrete - Part 2: Slump Test, 2019. Netherlands Standardization Institute.
Ngo, H.-T., Kadri, E.-H., Kaci, A., Ngo, T.-T., Trudel, A., Lecrux, S., 2016. Advanced online water content measurement for self-compacting concrete production in ready-mixed concrete plants. Constr. Build. Mater. 112, 570–580.
Omran, A.F., Naji, S., Khayat, K.H., 2011. Portable vane test to assess structural buildup at rest of self-consolidating concrete. ACI Mater. J. 108 (6).
Ren, B., Wang, H., Wang, D., Guan, T., Zheng, X., 2023. Vision method based on deep learning for detecting concrete vibration quality. Case Stud. Constr. Mater. 18, e02132.
Rong, X., Liu, H., Li, C., 2022. A proposed method and monitoring system for evaluating workability of Portland cement concrete during mixing. Heliyon 8 (11), e11355.
Roussel, N., 2007. Rheology of fresh concrete: from measurements to predictions of casting processes. Mater. Struct. 40 (10), 1001–1012.
Schack, T., Coenen, M., Haist, M., 2024a. Digital slump flow: image-based assessment of fresh concrete homogeneity as part of the slump flow test. Case Stud. Constr. Mater. 21, e03973.
Schack, T., Coenen, M., Haist, M., 2024b. Image-based quality control of fresh concrete based on semantic segmentation algorithms. Civil Eng. Des. 6 (3), 96–105.
Sheng, R., Yuan, Y., Zhang, J., Liu, Y., Yao, X., Tao, Y., Zhang, J.-L., 2026. An interpretable multimodal monitoring system for mixing process of printcrete: integrating computer vision, torque, and temperature. Cement Concr. Compos., 106685
Tahoun, M., Tahri, O., Ramón, J.A.C., Mezouar, Y., 2021. Visual-tactile fusion for 3D objects reconstruction from a single depth view and a single gripper touch for robotics tasks. In: 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 6786–6793.
Teng, L., Meng, W., Khayat, K.H., 2020. Rheology control of ultra-high-performance concrete made with different fiber contents. Cement Concr. Res. 138, 106222.
Tuan, N.M., Van Hau, Q., Chin, S., Park, S., 2021. In-situ concrete slump test incorporating deep learning and stereo vision. Autom. ConStruct. 121, 103432.
Wang, D., Ren, B., Cui, B., Wang, J., Wang, X., Guan, T., 2021. Real-time monitoring for vibration quality of fresh concrete using convolutional neural networks and IoT technology. Autom. ConStruct. 123, 103510.
White, C., 2025. Digital Rheology of fresh-state Concrete. PhD thesis. University of Cambridge.
White, C., Lees, J.M., 2023. Yield stress prediction from 3D reconstruction of fresh concrete slump. Cement Concr. Res. 174, 107331.
White, C., Lees, J.M., 2025. The concrete slump test—A rheometer by definition? Constr. Build. Mater. 462, 139839.
Wilenius, A., Karppinen, P., Pättö, J., 2020. Digital Concrete Quality Assurance: Possibilities for data-driven Quality Assurance of Concrete in Production. Väyläviraston julkaisuja.
Xie, H., Liu, F., Fan, Y., Yang, H., Chen, J., Zhang, J., Zuo, C., 2013. Workability and proportion design of pumping concrete based on rheological parameters. Constr. Build. Mater. 44, 267–275.
Yan, W., Cui, W., Qi, L., 2020. Effect of aggregate gradation and mortar rheology on static segregation of self-compacting concrete. Constr. Build. Mater. 259, 119816.
Yang, L., An, X., Du, S., 2021. Estimating workability of concrete with different strength grades based on deep learning. Measurement 186, 110073.
Yoon, J., Kim, H., Ju, S., Li, Z., Pyo, S., 2023. Framework for rapid characterization of fresh properties of cementitious materials using point cloud and machine learning. Constr. Build. Mater. 400, 132647.
Yoon, J., Kim, H., Li, Z., Jun, H., Kim, M., Wi, S., Park, J., 2026. Point cloud–ANN integrated framework for rapid predicting fresh properties of self-consolidating concrete. Case Stud. Constr. Mater., e06081
Zhao, K., Zhao, L., Hou, J., Zhang, X., Feng, Z., Yang, S., 2021. Effect of vibratory mixing on the slump, compressive strength, and density of concrete with the different mix proportions. J. Mater. Res. Technol. 15, 4208–4219.