



Delft University of Technology

Document Version

Final published version

Licence

CC BY

Citation (APA)

Premarathna, W. A. A. S., Kumar, A., Khan, F. R., Moenielal, M., Kasbergen, C., & Erkens, S. M. J. G. (2026). A study on the reconstruction of 3D asphalt surface replicas for statistically reliable analysis. *International Journal of Pavement Engineering*, 27(1), Article 2681680. <https://doi.org/10.1080/10298436.2026.2681680>

Important note

To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright

In case the licence states "Dutch Copyright Act (Article 25fa)", this publication was made available Green Open Access via the TU Delft Institutional Repository pursuant to Dutch Copyright Act (Article 25fa, the Taverne amendment). This provision does not affect copyright ownership.
Unless copyright is transferred by contract or statute, it remains with the copyright holder.

Sharing and reuse

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.

This work is downloaded from Delft University of Technology.



A study on the reconstruction of 3D asphalt surface replicas for statistically reliable analysis

W. A. A. S. Premarathna , Anupam Kumar , Fahim R. Khan , Mahesh Moenielal , Cor Kasbergen & Sandra M. J. G. Erkens

To cite this article: W. A. A. S. Premarathna , Anupam Kumar , Fahim R. Khan , Mahesh Moenielal , Cor Kasbergen & Sandra M. J. G. Erkens (2026) A study on the reconstruction of 3D asphalt surface replicas for statistically reliable analysis, International Journal of Pavement Engineering, 27:1, 2681680, DOI: [10.1080/10298436.2026.2681680](https://doi.org/10.1080/10298436.2026.2681680)

To link to this article: <https://doi.org/10.1080/10298436.2026.2681680>



© 2026 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.



Published online: 02 Jun 2026.



Submit your article to this journal [↗](#)



Article views: 312

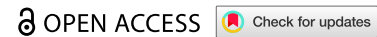


View related articles [↗](#)



View Crossmark data [↗](#)

RESEARCH ARTICLE



A study on the reconstruction of 3D asphalt surface replicas for statistically reliable analysis

W. A. A. S. Premarathna^a, Anupam Kumar^a, Fahim R. Khan^a, Mahesh Moenielal^b, Cor Kasbergen^a and Sandra M. J. G. Erkens^a

^aSection of Pavement Engineering, Faculty of Civil Engineering and Geosciences, Delft University of Technology, Delft, The Netherlands; ^bSection of Buildings, Materials and Structures, TNO, Delft, The Netherlands

ABSTRACT

Accurate replication of pavement textures is crucial for tire-pavement interaction studies in laboratory conditions, particularly at the macro-texture level. Existing replication methods often rely on costly equipment and lack standardized procedures for validating surface replicas. This study presents a novel methodology to replicate pavement surfaces and validation. The methodology integrates Mean Texture Depth (MTD) as a 3D texture indicator, silicone rubber casting technology, Finite Element (FE)-based 3D geometric calculations, and smartphone-video-based digital modelling using computer vision. Different asphalt mixtures with distinct surface textures were used for the development of the physical and digital replicas. Physical replicas were produced through silicone casting and epoxy moulding, while digital replicas were generated using the Structure-from-Motion technique. Validation was conducted using the standard sand patch test for physical samples and FE-based MTD calculations for digital models. The results showed strong agreement between the replicas and the original pavement samples. Statistical analyses confirmed normal distribution, variance homogeneity, and no significant differences between digital and physical samples. The findings of this study are expected to benefit road authorities in the design and laboratory testing of pavement surfaces, with the aim of evaluating pavement performance.

ARTICLE HISTORY

Received 27 January 2026
Accepted 25 May 2026

KEYWORDS

Pavement texture replication; macro-texture; silicone rubber casting; structure-from motion; computer vision; epoxy moulding

1. Introduction

The condition of pavement surfaces plays a critical role in both the quality of road infrastructure and the safety of its users. Among the many factors that define pavement performance, surface texture is particularly important, as it directly influences vehicle-pavement interaction (Huang & Huang, 2014; Kim et al., 2025). Surface texture describes the deviations of a pavement surface from an ideal flat plane, consisting of irregularities at different wavelengths that influence the interaction between the tyre and the pavement (I. S. O. 13473-2, 2002; Pranjic & Deluka-Tibljaj, 2022). Adequate surface texture not only enhances transportation safety but also contributes to improved vehicle fuel efficiency, making its preservation a key responsibility for pavement managers and road authorities. This permits a little scope for pavement designers to optimise surface characteristics in favour of reducing energy dissipation mechanisms, such as rolling resistance (RR) (Biffi et al., 2025; Gao et al., 2025; Liu et al., 2024), thereby contributing to both sustainability and performance improvements.

Rolling resistance is defined as the energy dissipated by the tyre per unit distance when a tyre rolls over a pavement surface (Sandberg et al., 2011; Sun et al., 2024), indicating that it is strongly influenced by the quality of the surface texture (Descornet, 1990). Past studies have shown that different levels of surface texture influence RR in distinct ways (Chen et al., 2022; Descornet, 1990; Levesque et al., 2023; Sandberg, 1990; Zhu et al., 2024). Surface texture levels are commonly classified according to the wavelength of the texture profile into four categories: micro-texture, macro-texture, mega-texture and unevenness (Chen et al., 2022). Among these, macro-texture and higher levels have been identified as having the most

significant impact on RR (Sandberg, 1990). In order to capture these surface texture effects, pavement engineering studies often employ texture parameters to quantify and describe the relationship between pavement surface and RR. MTD (International, 2015) is a commonly used volume-based parameter representing the average depth of surface irregularities (Ji et al., 2024; Ran et al., 2018; Song, 2022). Mean Profile Depth (MPD) (Characterization of pavement texture by use of surface profiles part 1) is another similar parameter to MTD, but is typically measured using different techniques (Lou et al., 2022; Pranjic & Deluka-Tibljaj, 2022; Zuniga-Garcia and Prozzi, 2019). Both MTD and MPD are key indicators of macro-texture, and their association with RR has been extensively studied (Sun et al., 2024). As a result, various empirical models have been developed using these parameters to predict RR (Ran et al., 2024; Sun et al., 2024).

In order to validate empirical models, researchers have developed a variety of field and laboratory methods for measuring RR, including trailer methods, drum tests of tyres, coast-down tests and fuel consumption approaches (Bergiers, 2011; Ejsmont et al., 2024; MIRIAM Project. (2010)). The trailer methods, coast-down methods and fuel consumption methods are used to collect RR measurements on real pavement surfaces in-field (Andersen et al., 2015; Bergiers et al., 2011; Hooghwerff et al., 2013; Sandberg et al., 2011; Świeczko-Żurek et al., 2017). In contrast, the test drum systems are utilised to collect the measurements in a laboratory environment (Andersen et al., 2015; MIRIAM Project. (2010)). Standard practice often relies on smooth steel-surfaced drums to measure RR in accordance with international guidelines (ISO 28580. (2009)). However, these surfaces poorly replicate the texture of real pavements, resulting in measurements that are not fully representative of in-field conditions (Ejsmont & Owczarzak, 2019; Ejsmont et al., 2025). Consequently, these measurements often introduce uncertainties and errors because they do not adequately account for the influence of different texture levels and parameters discussed above.

As described in previous paragraphs, RR measurements are significantly affected by the texture parameters. Therefore, a proper understanding of pavement texture and its quantification is essential for improving the accuracy of RR prediction. To address the limitations of smooth drum surfaces, researchers have proposed incorporating more representative pavement textures onto drum test facilities. One approach involved the development of a three-roadwheel facility using epoxy-based surface replicas of actual pavements (Ejsmont & Owczarzak, 2019; Ejsmont et al., 2024; Owczarzak et al., 2024; Ronowski, 2016). Owczarzak et al. (2024) further introduced a method for fabricating $50 \times 50 \times 20$ mm surface replicas using Polyethylene Terephthalate Glycol (PET-G) (Guessasma et al., 2019; Sepahi et al., 2021) through 3D printing technology. However, a major drawback of PET-G and other polymer-based materials is their susceptibility to excessive deformation under repeated tyre loading (Valvez et al., 2022). These excessive deformations can result from changes in mechanical properties due to moisture absorption and creep (Romeijn et al., 2021; Valvez et al., 2022), ultimately leading to alterations in surface texture and compromising the accuracy of RR measurements during extended testing. Alternatively, Ejsmont et al. (2025) developed surface-segment outfitting for drums using casting technology and assessed the validity of the replicas through 2D profile measurements and comparative RR tests. These physical replicas enable systematic investigation in a controlled environment by reducing the uncertainties and dependence on costly and time-intensive field studies. Despite these advances, existing studies have not explicitly demonstrated or validated the three-dimensional (3D) geometrical similarity of physical replicas to real pavement surfaces in terms of texture characteristics. To the best of the author's knowledge, this gap has not been adequately identified in the literature. In recent days, digital replicas have been increasingly explored as an alternative for similar applications (Srirangam et al., 2015; Tang et al., 2018).

Recent efforts have focused on integrating digital replicas with the finite element method (FEM) to construct digital twin models of tire-pavement interaction, offering an alternative to the costly and labour-intensive nature of conventional RR testing (Namjoo & Golbakhshi, 2015; Srirangam et al., 2015; Tang et al., 2018). A critical step in these FEM approaches is model validation, and the validation of FE-based tyre models has been extensively described in earlier studies (Al-Najati et al., 2024; Fathi et al., 2024; Ramji et al., 2023). However, limited attention has been given in the literature to geometrical validation methods for 3D digital pavement replicas with detailed texture. Typically, validation of tire-pavement interaction FEM models is carried out using parameters that capture aspects of motion and force transfer between the tyre and pavement (Mashadi et al., 2019; Srirangam et al., 2015; Tang et al., 2018). Srirangam et al. (2015)

validated their tire-pavement interaction model by comparing computed braking friction coefficients with field measurements on digital asphalt surface replicas. Although the above studies demonstrate the potential of digital replicas within FEM frameworks, their validation remains challenging. These models are computationally demanding due to the large number of elements, require specialised applications for mesh refinement, involve difficulties in isolating and debugging model components, necessitate advanced laboratory facilities, and demand significant model processing time.

As highlighted above, the validation of replicas plays a critical role in ensuring reliable data acquisition and, consequently, in improving the accuracy of systematic investigations. However, both physical and digital pavement replicas often lack rigorous validation, particularly with respect to their three-dimensional geometrical fidelity at the macro-texture level. This shortcoming arises from several challenges, including the absence of standardised methods for 3D texture comparison, the high computational cost and the complexity of validating digital models. Hence, this study focuses to scientifically develop a statistical approach to validate both physical and digital replicas of pavement surfaces. The approach will focus on 3D geometry validation at the macro-texture level by integrating 3D texture indicators of MTD, casting technology, and smartphone-video-based digital modelling. It is anticipated that this framework will not only enhance the reliability of texture-based data acquisition but also assist road authorities by reducing the cost and effort of field studies, minimising uncertainties in measurement, and providing the foundation for a cloud-enabled system for large-scale pavement surface monitoring in the future. In response to the background of the study and identified limitations, the following subsection outlines the aim and scope of the research.

1.1. Research goal and scope

The aim of this study is to develop a methodology that integrates MTD, casting technology and computer vision-based digital modelling using smartphone video to create and validate the geometry of pavement surface replicas at the macro-texture level. The applicability of the proposed methodology is demonstrated by creating and validating both physical and digital replicas of the captured morphology from a variety of pavement mixture types. Reproducing replicas with similar surface characteristics and validating their geometry at the macro-texture level using a combination of casting technology and smartphone-based video remains an unsolved problem. In order to address the problem and achieve the aim, the scope of the research is defined as follows:

- i. To create digital and physical replicas with similar surface characteristics of pavement surfaces using smartphone-video-based computer vision technology and casting techniques. The primary focus is to develop replicas of pavement surfaces by utilising a smartphone-based, cost-effective, user-friendly and reliable approach.
- ii. To geometrically validate the surface replicas described in (i) at the macro-texture level. The validation of physical replicas is conducted based on MTD calculations using the commonly used sand patch test. In this study, a procedure based on FE (hereinafter referred to as the FE-based MTD calculator) is developed to calculate the MTD values of different digital samples. This procedure is used to validate the digital replicas. This step focuses on laying the foundation for developing an approach to measure and validate replicated surfaces at the macro-texture level to support cloud-based data collection system.
- iii. To compare the accuracy of surface replica validations using different pavement sections with different types of surface morphology based on the approaches described in (i) and (ii). The main focus of this scope is to ensure the applicability of the proposed methodology under varying surface morphologies.
- iv. In this study, MTD will be used because it is geometrically simple and easily quantifiable. More complex 3D parameters, such as RMS, skewness, or power spectral density, require high-resolution, laboratory-based equipment and are more sensitive to data noise. In contrast, MTD enables low-cost, rapid field assessment without the need for specialised surface profilers or lasers. This aligns with the study's goal of developing a scalable, non-destructive and accessible methodology.

1.2. The innovative aspect of the research

The innovative aspects of the research are highlighted below:

- i. *Cost-effective and user-friendly surface replication approach*: Unlike conventional methods that require expensive and specialised equipment, this research proposes a low-cost and accessible technique using smartphone-video-based computer vision technology and casting methods. The proposed approach enables efficient and widespread adoption for pavement texture analysis.
- ii. *Integration of physical and digital validation*: The study presents a validation approach for both physical and digital replicas, ensuring that replicated surfaces accurately represent real pavement textures. The physical validation leverages the sand patch test, while the digital validation employs using FE-based digital MTD calculator, offering a comprehensive assessment approach.
- iii. *Scientific advancement in pavement surface evaluation*: The framework advances current methodologies by systematically reproducing and validating pavement surface replicas with high geometric fidelity at the macro-texture level. The integration of 3D texture indicators of MTD in both physical and digital validation adds accuracy and reliability to surface texture assessments.
- iv. *Elimination of human bias through automated random masking validation*: The study proposes a novel random masking technique to eliminate human subjectivity in visual validation processes. This automated method ensures objective, reproducible and unbiased assessment of texture similarity between reference asphalt samples and their corresponding replicas. By removing dependence on manual interpretation, the technique enhances the accuracy and credibility of the validation framework, representing a significant methodological advancement in pavement surface evaluation.
- v. *Applicability across different pavement surface morphologies*: By demonstrating the validation process on a variety of pavement sections with different surface morphologies, the study ensures that the proposed methodology remains applicable under varying texture conditions, enhancing its robustness and real-world applicability.
- vi. *Bridging the gap between field studies and controlled investigations*: The use of replicas minimises uncertainties associated with field studies, providing a controlled environment for systematic pavement texture investigations. This facilitates more accurate and repeatable research outcomes while reducing reliance on time-intensive field measurements and validation.

1.3. Structure of the paper

The study begins by establishing a research methodology that outlines its aim and scope. The subsequent sections describe the development of physical and digital replicas, along with a visual comparison to the physical core. Following this, the paper presents the calculation of relevant MTD measurements of surface samples using the standard sand patch test and FE-based MTD calculator (D. T. Netherlands. 4TU.Federation). The findings from these sections are then statistically analysed and interpreted in the results and discussion section. Finally, the paper concludes with a summary of key insights and suggestions for future research directions.

2. Overview of existing replication procedures

This section briefly describes existing techniques and procedures for developing pavement surface replicas. Several methods have been introduced to create the replicas, either physically or digitally (Chen et al., 2021; Chen et al., 2019; Dabous et al., 2025; Ejsmont et al., 2025; Huyan et al., 2020; Mahmoudzadeh et al., 2020; Owczarzak et al., 2024; Pruitt et al., 2016). Each method has its own strengths and limitations. In this study, the construction of pavement surface replicas was categorised into two main methods: (1) physical replication and (2) digital replication. Physical replication methods involve creating tangible copies of pavement surfaces using materials such as additive manufacturing materials, silicone, epoxy, or other casting substances replica (Ejsmont et al., 2025; Owczarzak et al., 2024). In contrast, digital replication methods utilise advanced imaging and scanning technologies, such as photogrammetry, structure from motion (SfM), laser scanning, structured light scanning, RGB-D sensing and interference fringe

techniques, to digitally capture and recreate pavement surfaces in a virtual environment (Mahmoudzadeh et al., 2020; Pruitt et al., 2016).

2.1. Casting technology-based replicas

Casting techniques involve pouring a liquid material into a mould that reflects the pavement's surface profile. The mould of the pavement surface is typically created using silicone rubber-based elastomer materials (Owczarzak et al., 2024). The choice of casting material significantly impacts the properties of the replicas and the fidelity of the surface texture reproduction. Polyurethane resins are frequently employed due to their versatility, ease of use and ability to capture fine surface details (Das & Mahanwar, 2020). However, selecting the appropriate polyurethane formulation is crucial, as different formulations exhibit varying degrees of viscosity, curing times and resulting surface hardness. Hence, properties of the formulation can influence the accuracy of texture replication. Epoxy resins are also used as casting materials due to their excellent mechanical strength and adhesion properties (Ejsmont et al., 2025; Owczarzak et al., 2024). However, their higher viscosity compared to polyurethane resins can hinder the accurate reproduction of intricate surface textures such as deep grooves or sharp irregularities. Studies used asphalt mixtures to create replica of the pavement surfaces (Pomoni & Plati, 2022; Qian et al., 2024; Wang et al., 2020).

There are significant disadvantages to making replicas using asphalt mixtures. The reproduced replicas can exhibit considerable variability in their properties due to changes in the mixture, difficulties in ensuring consistent replica quality, and challenges in maintaining the reproducibility of similar surface characteristics. Apart from the casting materials, the moulding technique itself plays a critical role (Singh & Singh, 2016). In order to accurately reproduce the original surface, precise moulding techniques such as vacuum casting are commonly used. The precise moulding techniques can help to minimise air bubbles and ensure an accurate surface texture. Conversely, less refined casting methods may result in imperfections that compromise the accuracy of the replica. In addition, the demoulding process itself may introduce minor alterations to the surface texture, particularly for complex or highly irregular macro-texture features. Mechanical stresses during separation or inadequate release conditions can lead to local deformation, tearing, or smoothing of fine surface details, thereby affecting the fidelity of the replicated surface. The curing process significantly influences the final surface properties of the replica (Bajčičák & Šuba, 2014; Persson et al., 2018). Careful control of temperature and humidity during curing is necessary to ensure consistent material properties and the quality of the surface (Bajčičák & Šuba, 2014). To the best of the author's knowledge, there are a limited number of studies that have used casting technology with detailed explanations to develop and validate replicas.

2.2. 3D printing technology-based replicas

3D printing can be categorised as a hybrid method because it is necessary to establish a 3D digital model of the surface samples to be printed (Gong et al., 2023; Owczarzak et al., 2025). 3D printing allows for the creation of replicas that might be difficult or impossible to achieve using traditional casting methods. Different 3D printing technologies, such as stereolithography (SLA), selective laser sintering (SLS), and fused deposition modelling (FDM), offer varying degrees of accuracy and resolution (Gao et al., 2015; Mechtcherine et al., 2019). The selection of appropriate printing parameters, including layer height, infill density and printing speed, impacts the surface texture and overall quality of the replica (Owczarzak et al., 2024). To the best of the authors' knowledge, there are very few studies on creating 3D-printed replicas of pavement surfaces. In pavement engineering, 3D printing has been typically used for the purpose of pavement maintenance perspective (Gong et al., 2023a, 2023b). Jackson et al. (2018) developed a 3D printer capable of extruding asphalt to create complex geometries and repair cracks in pavement surface layers. The study's findings revealed that 3D-printed asphalt exhibited nine times the ductility of cast samples while maintaining comparable fracture strength. A study tested the printability of composite-modified asphalt using a plunger 3D printer (Song et al., May 2025). The results indicated that the modified asphalt mixture has improved crack repair capability while maintaining moderate printing requirements. There are disadvantages of 3D printing related to the creation of surface replicas in the

pavement engineering domain. Asphalt 3D printing is challenging due to high viscosity and heating requirements (Song et al., May 2025). The significant drawback of the 3D printing approach is the printing time required for the samples. The printing time directly depends on the printing parameters, the size of the sample and the complexity of its geometry. The cost of 3D printing can be another limiting factor. The availability of suitable materials specifically designed for pavement replica applications remains relatively limited and is an area open to research.

2.3. Multi-source data fusion-based replicas

Image-based multi-source fusion technology is used to capture surface images and convert them into 3D point cloud models (Dan et al., 2023). The image-based fusion method is particularly beneficial for covering large areas. It provides a cost-effective way to obtain a detailed representation of pavement surface morphology. The main drawback is that the accuracy and overall quality of the 3D model can be influenced by factors such as lighting conditions, image quality and the presence of repetitive patterns or features on the pavement surface. The Image-based fusion approach typically involves multiple cameras or sensors capturing images from different viewpoints. The images are then processed using photogrammetry, SfM, RGB-D sensing or other 3D reconstruction techniques to generate a 3D point cloud representing the pavement surface (Dan et al., 2023; Jiang et al., 2024; Knyaz & Chibunichev, 2016; Lei et al., 2014; Pranjić & Deluka-Tibljša, 2022).

The SfM technique is gaining popularity in pavement engineering due to its ability to achieve high-accuracy digital geometries and serve as a cost-effective alternative to expensive 3D scanning technologies. It is particularly useful for reconstructing complex morphologies such as pavement surface macro-texture and potholes, where other techniques may face challenges. A SfM-based reconstruction method combined with deep learning was proposed to obtain texture depth information and evaluate the skid resistance of asphalt pavement (Dan et al., 2024). The study used images of the surface, volume-based metric of MTD and SfM-based approach to obtain texture depth information using digital replicas of pavement surfaces. Ronald et al. (Roberts et al. 2020) utilised the SfM technique with smartphone-based images to reconstruct pavement surfaces and assess the level of pavement distress. A 2D image-based damage detection system for pavement potholes was developed using SfM-based 3D surface reconstruction and convolutional neural network-based segmentation techniques (Wang et al., Sep. 2023). Despite the advancements, a detailed description of the validation process for their 3D replicas of the pavement surface is missing from these studies.

2.4. 3D scanning-based replicas

Laser scanning techniques and structured light scanning are widely used in pavement engineering to create 3D replicas of pavement surfaces. In structured light scanning, projects a known pattern of light onto the pavement surface and captures the deformed pattern with a camera (Knyaz & Chibunichev, 2016). The three-dimensional coordinates of points on the surface are calculated with high accuracy and resolution by analysing the distortion of the projected pattern. The method of structured light scanning is particularly effective for capturing fine details of the pavement surface. However, its applicability is limited by the system's design, scanning range and the need for controlled lighting. On the other hand, laser scanning techniques, including high-precision scanners and triangulation methods, provide a powerful approach for characterising pavement texture (Bitelli et al., 2012; Clapp & Eberhardt, 1986). Laser scanning employs laser beams to precisely measure the distance to the pavement surface, generating a dense 3D point cloud (Jiang et al., 2024; Liang et al., 2024). The laser scanners enable comprehensive 3D analysis of pavement morphology (Bitelli et al., 2012). Its high precision enables the accurate capture of both macro-texture and micro-texture features, providing detailed information about the pavement surface. Leng et al. (2023) enhanced the accuracy of 3D pavement texture reconstruction using interference fringes, significantly reducing reconstruction errors. The method offers high precision and resolution, making it particularly useful for measuring large areas such as pavement surfaces (Leng et al., 2023). However, laser scanning systems can be costly and are often sensitive to environmental factors such as weather conditions and the

presence of dust or debris (Leng et al., 2023). Additionally, processing the large datasets generated by laser scanning can be computationally demanding, requiring specialised software and hardware.

It is noted that the overall accuracy of pavement surface replicas produced using the above procedures is influenced by the accumulation of errors across multiple stages of the replication process. These include uncertainties associated with 3D surface acquisition techniques, such as photogrammetry or scanning, as well as errors introduced during physical reproduction processes, including moulding, material behaviour and demoulding. In particular, existing 3D modelling approaches may exhibit limitations in accurately capturing fine-scale surface details, especially at the macro-texture level, due to factors such as resolution constraints, noise and reconstruction algorithms. The combined effect of these factors may lead to deviations between the original surface and its replica, highlighting the importance of rigorous validation methods.

3. Research methodology

As illustrated in Figure 1, the study was conducted in four phases. In Phase I, the preparation of pavement samples with five distinct asphalt mixtures was carried out. In Phase II, both digital and physical replicas of the samples were reproduced. In Phase III, focus was given on calculating the corresponding MTD of the samples in Phase II using standard sand-patch test (ASTM International, 2015) and FE-based MTD calculator. Finally, in Phase IV, validation and comparison of the results were carried out based on the outcomes obtained in Phase III. Detailed descriptions of the tasks performed in each phase are presented in the following sub-sections.

3.1. Phase I: preparation of pavement samples

In this phase, the pavement samples were collected from a highway road section in the Netherlands. These samples were cleaned and prepared to produce corresponding replicas to be used in the Phase II to Phase III. To demonstrate the applicability of the proposed methodology, five different pavement samples were selected, which are Mixture 1 (DZOAB16-Dense-Graded Porous Asphalt Concrete), Mixture 2 (2L-ZOAB5 -Durable ZOAB, Porous Asphalt), Mixture 3 (DA-Dense Asphalt), both Mixture 4 and Mixture 5 (ZOAB16-treated with rejuvenation). It is noted that the Mixture 1 was selected as a single-layer porous asphalt mixture with a 16 mm nominal aggregate size, providing a very coarse surface texture.

In contrast, Mixture 2, was selected as a double-layer porous asphalt mixture, where the 5 mm aggregate yields a very fine surface texture. Mixture 1 exhibited higher air void content due to the larger aggregate size compared to Mixture 2. Mixture 3 was a relatively new dense asphalt sample, providing a finer surface texture compared to Mixture 2. Mixture 4 and Mixture 5 were worn ZOAB16 samples that had been treated with rejuvenation. As a result, their surfaces were smoother and more closed than the other mixture types, as the rejuvenation coating partially filled the macrotexture. The samples were cleaned, and all debris was removed before proceeding to the remaining Phases.

As shown in Figure 2(a) and (b), the outer boundary of the sample core was covered and sealed with a reinforced paperboard ring. This was done to securely contain the liquid silicone rubber used in Phase II. For clarity and due to space limitations, the detailed methodological steps presented in the following subsections focus only on Mixture 1 and Mixture 2. It is noted that the same procedures were followed to obtain the physical and digital replicas for Mixtures 3, 4 and 5.

3.2. Phase II: production of pavement surface replicas

In this phase, physical replicas of the pavement samples were first created using casting technology as shown in Figure 2. Thereafter, digital replicas (see Figure 3) were generated using smartphone-video-based computer vision technology.

At first, the physical replicas were developed by pouring translucent silicone rubber mixture to the samples that were prepared in Phase I. A specific releasing agent was applied on the surface samples before pouring the liquid silicone rubber. It is noted that the purpose of adding the releasing agent was to facilitate the smooth demoulding process without damaging the silicone mould. After pouring the liquid

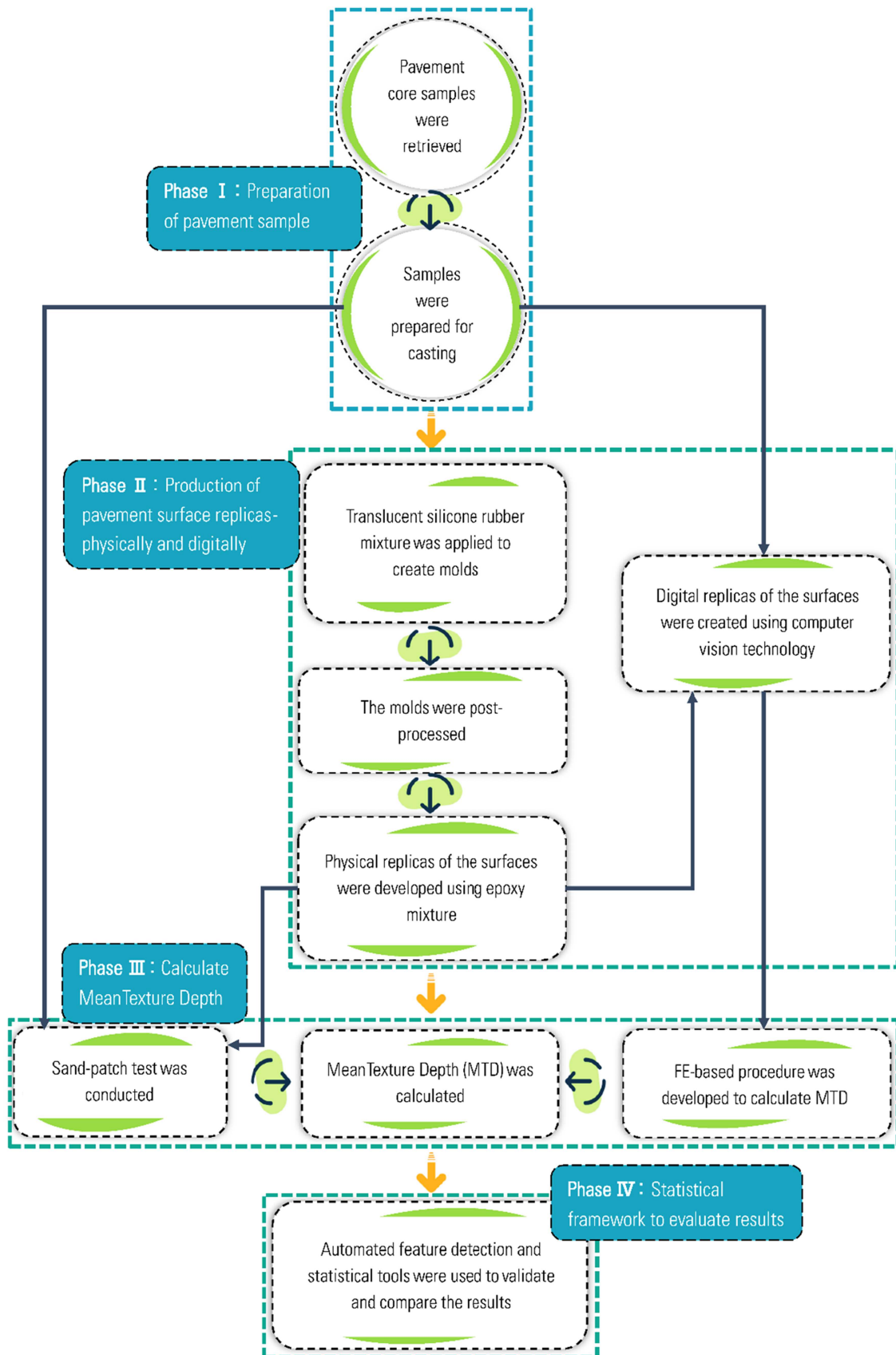


Figure 1. Research methodology.

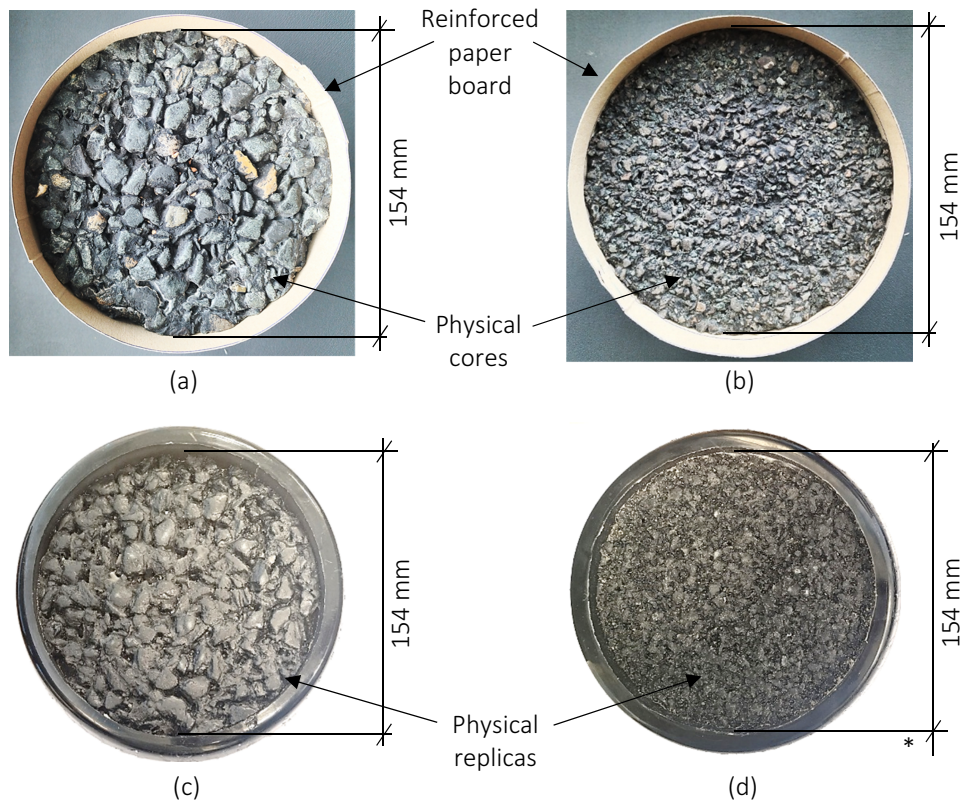


Figure 2. Pavement cores and physical replicas with different surface morphologies: (a) pavement core-mixture type 1, and (b) pavement core-mixture type 2, (c) physical replica of Mixture 1 and (d) physical replica of Mixture 2.

silicone the samples were kept at room temperature for 3 hours to allow the mould to fully harden. The hardened silicone mould was then cleaned and prepared to develop physical replicas using a specific epoxy mixture as presented in Figure 2(c) and (d). The mould with liquid epoxy mixture was placed at room temperature ($\sim 25^{\circ}\text{C}$) for 7 - 8 hours to allow the models to fully harden.

After obtaining the physical replicas, the digital replicas were created utilising computer vision technology and recorded smartphone-based videos as illustrated in Figure 3. The video footage of the target surface was recorded under uniform lighting conditions to minimise shadows and reflections that could affect feature detection. The recording process aimed to capture features of the individual surface from multiple viewpoints to ensure comprehensive geometric and textural coverage. During data collection, the phone was held at varying angles around the sample, following a semi-circular or orbital path. The mobile device was handheld but moved smoothly around the sample to avoid abrupt camera motion. The distance between the camera and the sample was kept approximately constant to maintain a uniform scale across frames. The camera was positioned at an angle ranging between approximately 30° – 60° relative to the surface normal to ensure adequate visibility of surface features and depth variations from multiple perspectives, which is essential for reliable Structure from Motion-based 3D reconstruction. The 3D digital models were generated solely from smartphone-recorded video, therefore, ensuring sufficient frame overlap and comprehensive surface coverage was a key requirement. In SfM-based modelling, accurate reconstruction depends primarily on image overlap and feature visibility rather than a fixed camera angle. The recording was performed using a handheld approach without a fixed mount, allowing flexible coverage of the sample surface. During acquisition, the smartphone was moved smoothly from close-range views to wider perspectives while varying its position within the specified angular range to capture all relevant surface characteristics. This angular range ensures that key visual details are adequately captured while avoiding perspective distortion. The videos were recorded at a resolution of 3840×2160 pixels (4K UHD), aspect ratio of 16:9 and a frame rate of 60 frames per second (fps) to preserve fine spatial detail and reduce motion blur. The recording path covered both horizontal and slightly elevated

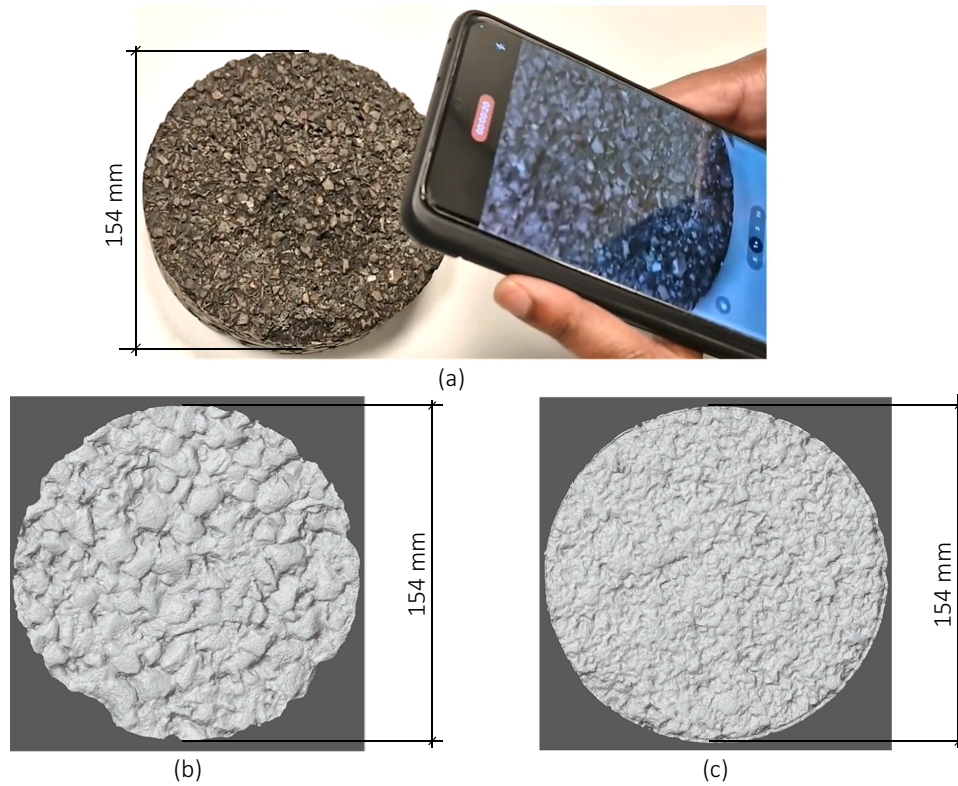


Figure 3. Development of digital replicas: (a) video recording process using a smartphone, (b) digital replica of Mixture 1 and (c) digital replica of Mixture 2.

viewpoints, providing sufficient overlap between consecutive frames for robust feature matching during reconstruction. Each recording session lasted approximately 40 -60 seconds.

Environmental conditions such as lighting intensity and background clutter were controlled to improve the clarity of captured frames. The resulting video dataset was subsequently used for frame extraction and 3D reconstruction using SfM technique (Schönberger & Frahm, 2016; Schönberger et al., 2016, 2017). The post-processing and mesh-refinement steps were followed to obtain 3D digital replicas. Poisson surface reconstruction (Kazhdan et al., 2006) was employed to generate surface meshes with triangular elements (Lo, 2002) and refine the surface topology from noisy point clouds. The radius outlier removal technique (Duan et al., 2021; Le et al., 2023; Szutor & Zichar, 2023) was applied to eliminate points with insufficient neighbouring data within a specified radius. The neighbouring points refer to points located within a defined spherical radius around a given point in the 3D point cloud. If the number of neighbouring points within this radius falls below a specified minimum threshold, the point is considered to have insufficient neighbouring data and is classified as an outlier. Such points typically arise due to noise, reconstruction errors, or isolated measurements and do not represent the true surface geometry. Therefore, removing these sparsely distributed points improves the quality and reliability of the reconstructed surface by ensuring a more continuous and consistent point cloud. Subsequently, the mesh coordinates were rescaled to standard units to ensure consistency across all datasets. The purpose of the data preprocessing stage was to ensure the quality of the gathered data while also enabling correct transformation for further analysis in Phase III and Phase IV. The digital replicas of the pavement core samples are presented in Figure 3(b) and (c). Both digital and physical replicas were used in Phase III and Phase IV to calculate the MTD and validate the process against real samples.

3.3. Phase III: MTD calculation

The corresponding MTD of the physical samples in Phase II were calculated using standard sand-patch test (ASTM International., 2015). The MTD of digital samples were calculated using FE-based MTD

calculator (see Equation (1)). During the sand spreading process, consistency was maintained across corresponding regions of both the physical core and the physical replica (see Figure 4).

$$MTD = \frac{4V}{\pi D^2}, \quad (1)$$

where:

MTD: mean texture depth (mm),

V: volume of sand used (mm³),

D: average diameter of the sand patch (mm).

The digitalisation setup of the sand-patch test for the digital samples is presented in Figure 4. To simulate the sand patch test on digital samples, tetrahedral (4-node) elements were generated to fill the volume below the reference plane, as shown in Figure 4. If the total number of elements used to fill the void is 'n', then the volume (V_1) was calculated using Equation (2).

$$V_1 = \sum_i^n \frac{1}{6} | \det(M) |, \quad (2)$$

$$V = V_1, \quad (3)$$

where:

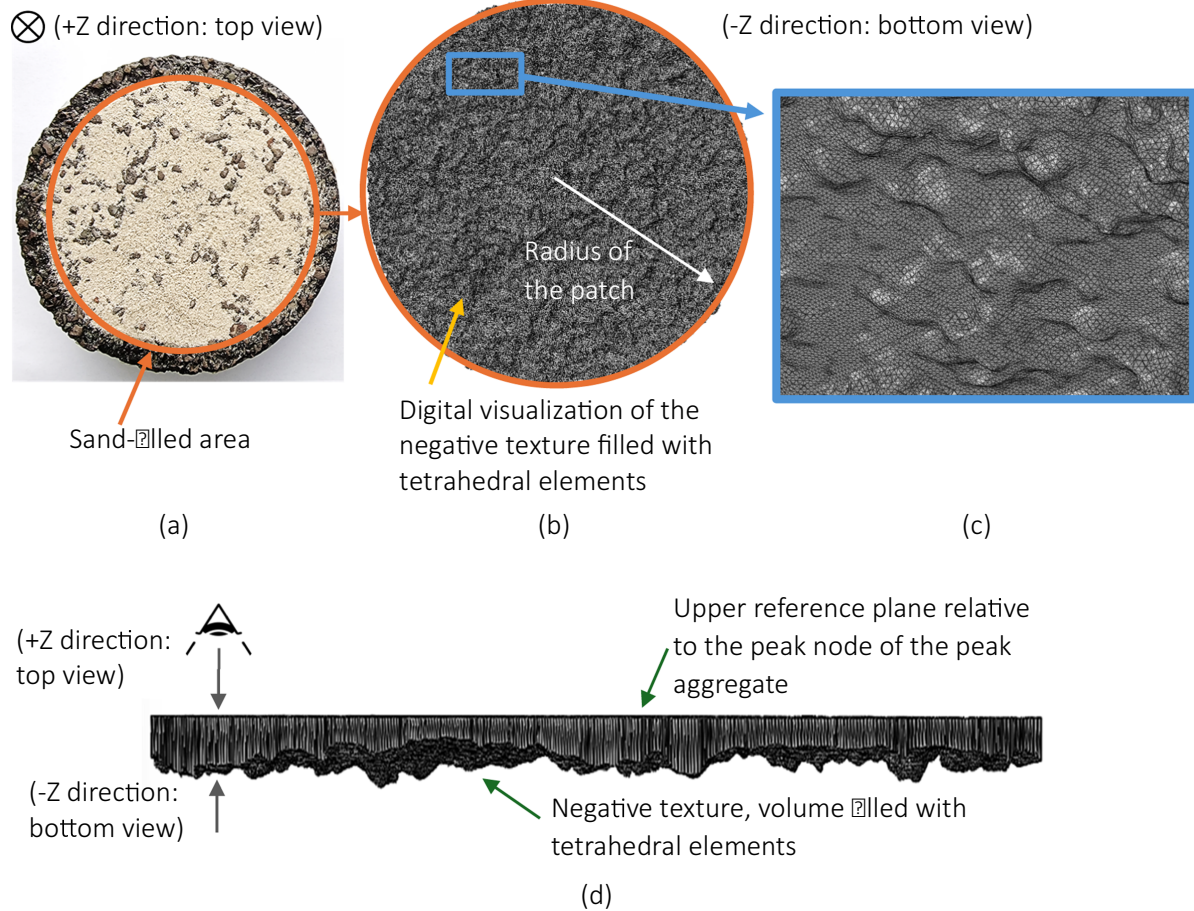


Figure 4. Digital simulation of sand-patch test: (a) visualisation of sand-filled area on physical core, (b) digital simulation of the sand patch test, (c) zoomed-in view of the negative texture filled with finite elements and (d) side view of the digital visualisation.

$$M: \begin{bmatrix} B_x - A_x & B_y - A_y & B_z - A_z \\ C_x - A_x & C_y - A_y & C_z - A_z \\ D_x - A_x & D_y - A_y & D_z - A_z \end{bmatrix},$$

V_1 : Total volume covered by individual tetrahedral element (mm^3).

A, B, C, D : The vertices of a tetrahedral element and the coordinates of its four nodes can be represented as $A (x_1, y_1, z_1)$, $B (x_2, y_2, z_2)$, $C (x_3, y_3, z_3)$ and $D (x_4, y_4, z_4)$.

It is noted that the size of the tetrahedral elements may influence the calculated MTD values, as larger elements can partially fill surface voids while smaller elements provide a more detailed representation of the surface geometry. In this study, a tetrahedral mesh was generated using an adaptive mesh generation approach. In this procedure, smaller elements were assigned to regions with higher surface curvature, sharp texture variations and complex void geometry, while larger elements were used in smoother regions. This allowed the main macro-texture features to be captured with sufficient geometric resolution while avoiding unnecessary computational cost. Different mesh refinement levels were examined during the development stage, and the adopted mesh was selected once further refinement produced only negligible changes in the calculated MTD values. Furthermore, the FE-based MTD calculations were validated against the results obtained from the physical sand patch tests, and the good agreement observed indicates that the chosen mesh discretisation provides a reliable representation of the surface geometry.

3.4. Phase IV: statistical approaches to evaluate the results

In Phase IV, validation and statistical analyses were conducted, which are presented in the following section. The distributions of MTD data and descriptive statistics were calculated and analysed using statistical tools such as box plots (Wickham & Stryjewski, 2011), the Shapiro–Wilk test (Shapiro & Wilk, 1965) and Levene's test (Levene, 1960). It is noted that parametric analyses were conducted after confirming that the data followed a normal distribution. To compare similarities among the four categories of Physical core, Physical replica, Digital core (a digital replica of Physical core) and Digital replica (a digital replica of Physical replica), data analyses were conducted for three group pairs for both Mixture 1 and Mixture 2: Physical core and Physical replica, Physical core and Digital core, and Physical replica and Digital replica. To maintain comparability across samples, surface sections of consistent size (diameter of 154 mm) were considered across all samples to ensure comparability. The similarity between the Physical Core, Physical Replica, Digital Core and Digital Replica was evaluated based on a statistical comparison of MTD values obtained from corresponding localised regions. Specifically, repeated measurements were conducted on each sample, and similarity was assessed using descriptive statistics and distribution-based comparisons. In addition, statistical tests such as the Kolmogorov–Smirnov (An, 1933), Anderson–Darling (Anderson and Darling, 1954) and Cramér–von Mises (Cramér, 1928) tests were employed to evaluate the similarity of data distributions between corresponding sample pairs. Finally, a comprehensive discussion was carried out based on the validation accuracy of the replicas and the applicability of the proposed methodology.

4. Results and discussion

The key outcomes, aligned with the phases described in the methodology, are presented in this section.

4.1. Validation using random sampling and masking technique

In order to eliminate human bias in visual validation, this study introduces a random masking technique, as validation processes involving human intervention are inherently limited in objectivity. Human-based visual inspection is intrinsically subjective and may exhibit considerable variability among evaluators, thereby compromising the consistency and reliability of the outcomes. Furthermore, manual visual validation is both time-intensive and unsuitable for large-scale datasets. Consequently, an automated

and randomised approach employing random sampling and masking techniques was implemented to assess the similarity of features between Physical Cores and their corresponding Physical Replicas.

As shown in Figure 5, a random masking technique was used to compare the original Physical Cores with their corresponding Physical Replicas. An automatic feature recognition application was created to identify and track similar surface features between the core and the corresponding replica. The locations of these features were randomly selected, and the corresponding areas were highlighted using circles, as presented in Figure 5. The initial visual validation was performed manually with human intervention. Upon satisfactory confirmation, automated feature correlation was subsequently conducted using computer vision techniques (OpenCV). This process involved a visual comparison of the surface morphologies between the Physical Core and its corresponding Physical Replica. To eliminate bias associated with the mixture type, all image data were compiled into vector forms $X_{i=1, \dots, n} M_{j=1, \dots, k}$ and $X'_{i=1, \dots, n} M_{j=1, \dots, k}$ during the data pre-processing stage. Where X_i represents the space of random locations in the Physical Core, X'_i represents the space of random locations in the Physical Replica, M_j denotes the random mixture type, n is the number of samples and k is the number of mixtures. On the basis of the automated technique conducted at random locations, as shown in Figure 5, it was observed that the Physical Replicas exhibit a strong agreement with their corresponding Physical Cores. This automated validation approach is proposed as a simple and practical method that can be readily adopted by road agencies and researchers to manually verify the similarity of surface samples. Although more advanced technologies, such as convolutional neural networks (CNNs) and other computer vision techniques, could be applied to enhance image-based similarity analysis. However, these methods typically require large datasets of surface samples, which were not available for the current study. Hence, the application of such advanced image analysis techniques lies beyond the scope of this paper.

4.2. Analysis of preliminary descriptive statistics

Following the method described in Phase III, 110 MTD tests were carried out on all physical samples. Correspondingly, for digital samples ($X_i M_j$ and $X'_i M_j$), 110 MTD values were also calculated using the FE-based 3D geometry calculation technique described in the previous Section 3.3. A total of 220 MTD values were obtained across all physical and digital samples. For each individual sample (Physical Core, Physical Replica, Digital Core and Digital Replica), 11 repeated MTD measurements were conducted. The reference MTD values for each mixture were calculated as the average of repeated measurements conducted on the corresponding Physical Core samples. Due to the limited specimen diameter of 154 mm, the measurements were performed on carefully selected localised regions distributed across the surface. Corresponding regions were maintained between the original samples and their replicas to ensure consistency and comparability in the analysis. The MTD values of the samples were plotted by assuming the Physical Core as the reference condition, as shown in Figure 6. For clarity and to illustrate the methodology effectively, the comparative results presented in this subsection focus on Mixture 1 and Mixture 2. It is noted that the same analysis steps were applied consistently to Mixtures 3, 4 and 5. As described previously (Section 3.1), Mixture 1 exhibited higher air voids due to its larger aggregate size compared to Mixture 2, which was expected to result in higher MTD values. As shown in Figure 6(a) and (b), Mixture 1 had higher MTD values than Mixture 2, which is consistent with findings reported in the literature (Song, 2022).

Another important observation from Figure 6 is that both Physical and Digital Replicas exhibited MTD value patterns similar to those of their corresponding Physical Cores. For example, in Figure 6(a), Sample 9 shows the lowest MTD value, which was consistently reflected across all other MTD values of the replicas. A similar behaviour was also observed in Figure 6(b) for Mixture 2. The MTD values of the Physical Replica, Digital Replica and Digital Core (see Section 3.4) closely followed those of the Physical Core, indicating that the replication techniques successfully preserved the surface texture characteristics.

To determine the absolute difference between the reference sample and the replicas, a quantitative evaluation was carried out by calculating the absolute percentage error using the data presented in Figure 6. The error was calculated by comparing the MTD values of the replicas with the corresponding Physical Core values, which were considered as the reference condition. The absolute error was obtained as

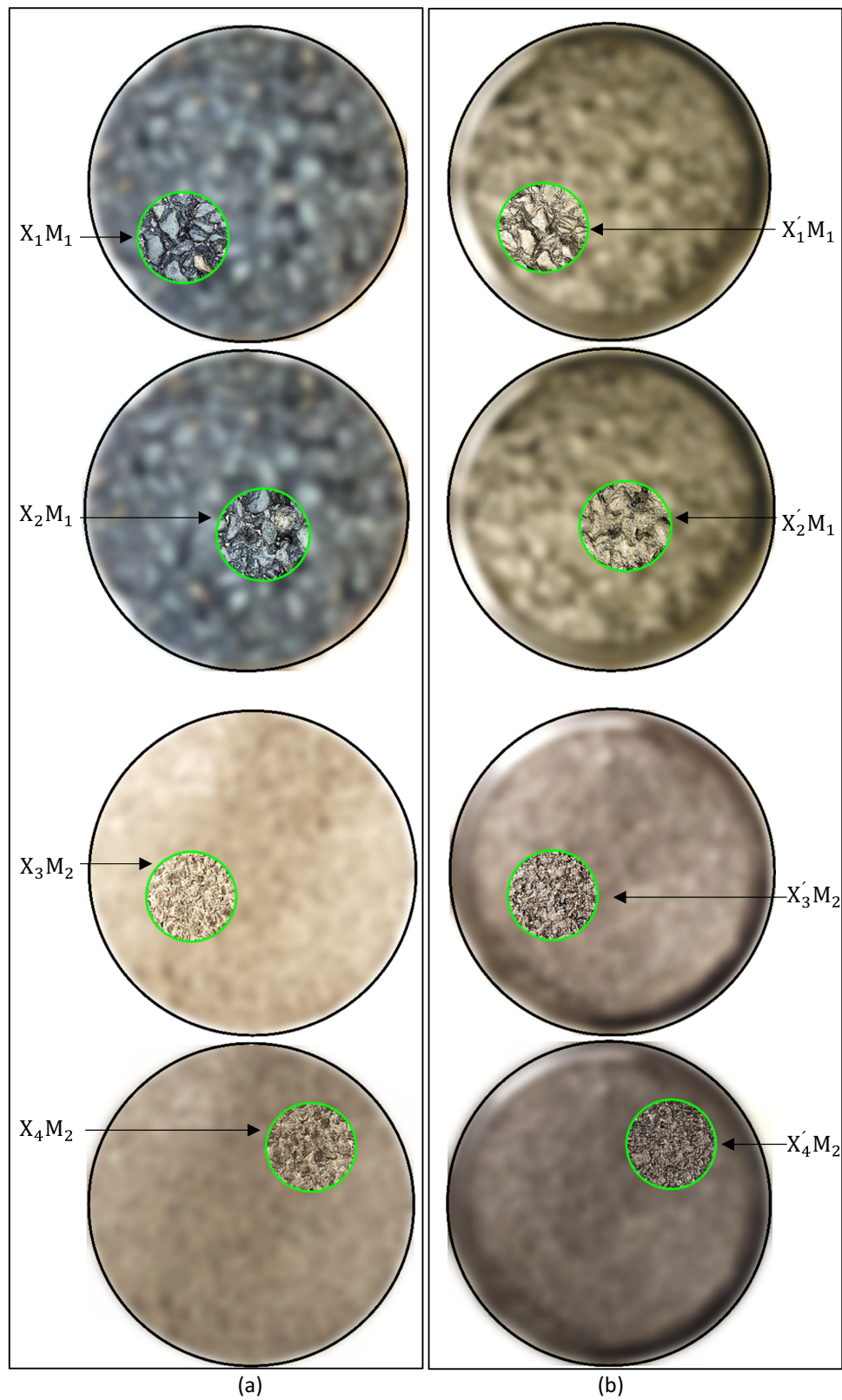


Figure 5. Visual validation of physical samples: (a) feature analysis of random locations in physical cores and (b) feature analysis of random locations in physical replicas.

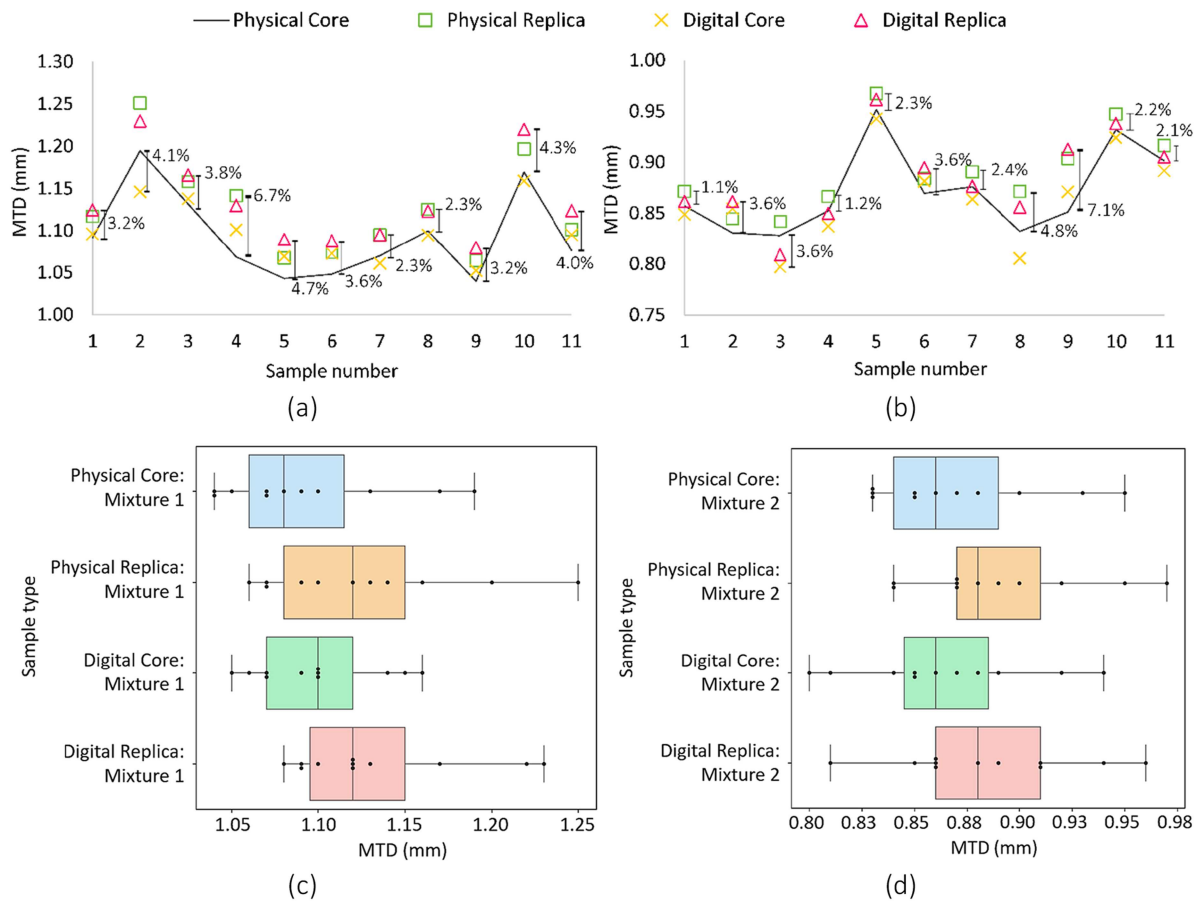


Figure 6. Comparison of MTD values: (a) visualisation of MTD in relation to sample number for Mixture 1, (b) visualisation of MTD in relation to sample number for Mixture 2, (c) box plots of four data categories for Mixture 1 and (d) box plots of four data categories for Mixture 2.

the difference between the replica and reference MTD values, and the absolute percentage error was calculated by normalising this difference with respect to the reference value and expressing it as a percentage. The absolute percentage errors of the replicas with respect to the Physical core generally remained below 5%, indicating a high level of accuracy in the replication process. Mixture 2 displayed slightly greater variability, with errors ranging between 1.1% and 7.1%, whereas Mixture 1 showed more stable and lower discrepancies, mostly within the range of 2.3%–6.7%. Since this study focused on macrotexture, the differences between the physical samples and their corresponding replicas were minimal and the errors remained within practical limits. These results therefore confirmed that both the digital and physical replication techniques reliably preserved the surface texture characteristics of the reference samples. It is noted that the variability observed in the MTD measurements is consistent with the known reproducibility limits of the sand patch test method. The differences between the Physical Core and corresponding replicas fall within the expected range of experimental variability associated with MTD measurements, indicating that the observed discrepancies are not solely due to the replication process but also reflect inherent measurement uncertainty. This further supports the consistency and reliability of the results obtained in this study.

As described in the previous paragraph, the absolute difference only summarises the percentage error between the reference sample and the corresponding replica and does not provide any statistical insight into data variability. To obtain this statistical information, the interquartile range (IQR), median and potential outliers were analysed and visualised using box plots, as shown in Figure 6(c) and (d). These plots provide a statistical basis for assessing whether the corresponding samples adequately represent the reference sample.

As expected, Mixture 1 consistently exhibited higher median MTD values across all four categories, indicating a coarser surface texture compared to Mixture 2, as discussed previously. In all categories of Mixture 1, the lower whiskers were relatively short, indicating that the minimum MTD values were close to the lower quartile and thus there was less variation on the lower end of the data. Conversely, the upper whiskers were notably longer, suggesting a greater spread or variability in the higher MTD values. This asymmetric whisker pattern indicated that while the lower range of texture depths was quite consistent across samples, the upper range exhibited more variability. In contrast to Mixture 1, the box plots for Mixture 2 showed the IQR values more centrally between the lower and upper whiskers, indicating a more symmetric distribution of MTD values and suggesting balanced variability on both sides of the median. This relatively symmetric distribution may be attributed to the finer aggregate size and more uniform surface characteristics of Mixture 2.

The median MTD values observed in the box plots indicated alignment between different data categories within each mixture. In Mixture 1, the medians of the Physical replica and Digital replica categories were closely aligned, indicating good agreement between the physical replication process and the corresponding digital analysis. In Mixture 2, a relatively stronger pattern of consistency was observed, where both the Physical core and Digital core, as well as the Physical replica and Digital replica, exhibited closely aligned medians. This suggests that Mixture 2 exhibited more uniform and reproducible surface texture characteristics across both physical and digital domains, potentially due to its finer aggregate structure.

4.3. Analysis of normality and distribution

The IQR provides insight into the central spread of the data but has limited capability to capture the full characteristics of the distribution, such as variance homogeneity and normality of the different sample categories. These statistical properties have direct implications for the reliability of surface texture characterisation within the context of pavement engineering. The normality of the MTD distribution supports the assumption that surface texture variations arise mainly from inherent material heterogeneity rather than systematic experimental or methodological bias. It is noted that a normally distributed MTD dataset indicates that the texture measurements are consistent and representative of the true surface characteristics of the mixture. This is particularly important when MTD values are later used for modelling pavement performance indicators such as rolling resistance, which are sensitive to texture variability. In contrast, variance homogeneity across the physical and digital samples ensures that the variability in MTD is comparable among the different measurement techniques. In pavement texture analysis, this means that the digital and physical replication processes introduce similar levels of uncertainty, validating the equivalency of the measurement methods.

In order to assess the underlying distribution and variance equality of the MTD data, statistical tests such as Levene's test (Levene, 1960) and the Shapiro-Wilk (Shapiro & Wilk, 1965) test were conducted. Assessing normality was essential for evaluating the reliability of the means and standard deviations used in parametric analyses. These tests served as critical prerequisites for selecting appropriate parametric or non-parametric methods for comparative analysis in this study. Levene's test was conducted to assess the assumption of variance homogeneity across the different categories within mixture types. The null hypothesis (H_0) was set as all groups have equal variances (homoscedasticity), while the alternative hypothesis (H_1) was set as at least one group has a different variance (heteroscedasticity). As given in Table 1, the p -values for all mixtures were significantly greater than the significance level of 0.05. Therefore, the null hypothesis could not be rejected for any of the mixtures. It indicates that the variances across the groups are statistically equal.

Table 1. Levene's test.

Mixture type	Levene's test statistics	p -value	Status of the hypothesis
Mixture 1	0.4386	0.7266	Fail to reject H_0 : variances are equal
Mixture 2	0.0251	0.9945	Fail to reject H_0 : variances are equal
Mixture 3	1.8348	0.1564	Fail to reject H_0 : variances are equal
Mixture 4	0.8933	0.4530	Fail to reject H_0 : variances are equal
Mixture 5	1.4933	0.2310	Fail to reject H_0 : variances are equal

Table 2. Shapiro–Wilk test.

Mixture type	Group	<i>W</i> statistics	<i>p</i> -value
Mixture 1	Physical core	0.894	0.157
	Physical replica	0.920	0.321
	Digital core	0.920	0.322
	Digital replica	0.845	0.136
Mixture 2	Physical core	0.890	0.138
	Physical replica	0.922	0.336
	Digital core	0.973	0.914
	Digital replica	0.967	0.858
Mixture 3	Physical core	0.916	0.285
	Physical replica	0.938	0.503
	Digital core	0.878	0.097
	Digital replica	0.925	0.363
Mixture 4	Physical core	0.922	0.338
	Physical replica	0.878	0.098
	Digital core	0.943	0.553
	Digital replica	0.917	0.291
Mixture 5	Physical core	0.896	0.165
	Physical replica	0.947	0.609
	Digital core	0.912	0.253
	Digital replica	0.881	0.108

The Shapiro–Wilk test was employed to assess whether the MTD data in each group were obtained from a normally distributed population. In this test H_0 assumed that the data were normally distributed, while the H_1 suggested a deviation from normality. As shown in Table 2, all sample groups exhibited *p* values greater than 0.05, indicating that the null hypothesis could not be rejected for any group. In addition, the *W*-statistics values for all groups were close to 1, suggesting that the data closely followed a normal distribution. The results confirm that the assumption of normality was satisfied for all groups. Therefore, the use of parametric statistical tests (such as *t*-tests) is appropriate for subsequent comparative analysis of the MTD data.

As shown in Figure 7(a), the calculated mean values for the Physical core, Physical replica, Digital core and Digital replica were $\bar{x}_1 = 1.094$, $\bar{x}_2 = 1.126$, $\bar{x}_3 = 1.099$ and $\bar{x}_4 = 1.134$, respectively, for Mixture 1. As shown in the corresponding figure, the curves appeared to be symmetrical about their means, indicating normality in the data distributions. It was also observed that the curve corresponding to the Digital core exhibited the highest density and was more concentrated around the mean. Moreover, it had the lowest standard deviation of 0.037 mm among the four groups, suggesting lower variability and higher consistency in the MTD values for the Digital core. In contrast, the Physical replica had the highest standard deviation (0.059 mm), reflecting slightly more variation in its measurements. The standard deviations for the Physical core (0.050 mm) and Digital replica (0.051 mm) fell in between, indicating moderate consistency.

The mean values and MTD distributions of the Physical core and Digital core were relatively close to each other, suggesting a good agreement between the physical specimen and its digital representation. Similarly, the Physical replica and Digital replica also showed closely aligned means and similar distribution shapes, indicating that the replication process and digital modelling were in strong agreement in terms of texture depth characteristics. The slight variations observed among the groups were still within acceptable engineering tolerances for surface texture characterisation.

As shown in Figure 7(b), the groups of Mixture 2 exhibited normal distribution patterns, with mean values of $\bar{x}_1 = 0.871$, $\bar{x}_2 = 0.891$, $\bar{x}_3 = 0.865$ and $\bar{x}_4 = 0.885$ for the Physical core, Physical replica, Digital core and Digital replica, respectively. The probability density curves for all four groups displayed similar peak heights, indicating uniformly low variability across the dataset and a consistent concentration of values around the means. In addition, the curves for the four groups were closely clustered, with standard deviations ranging from 0.041 mm to 0.043 mm. The mean values and distribution shapes of the Physical core and Digital core, as well as those of the Physical replica and Digital replica, were closely aligned. As shown in Figure 7, the groups of all mixtures demonstrated a strong correlation and a high level of agreement between the physical specimens and their corresponding digital models in terms of surface texture characteristics.

4.4. Verification of physical and digital replicas

A deeper investigation of MTD value comparisons between Physical and Digital replicas was done using three sets of sample pairs, which are ‘Physical core–Physical replica’, ‘Physical core–Digital core’ and

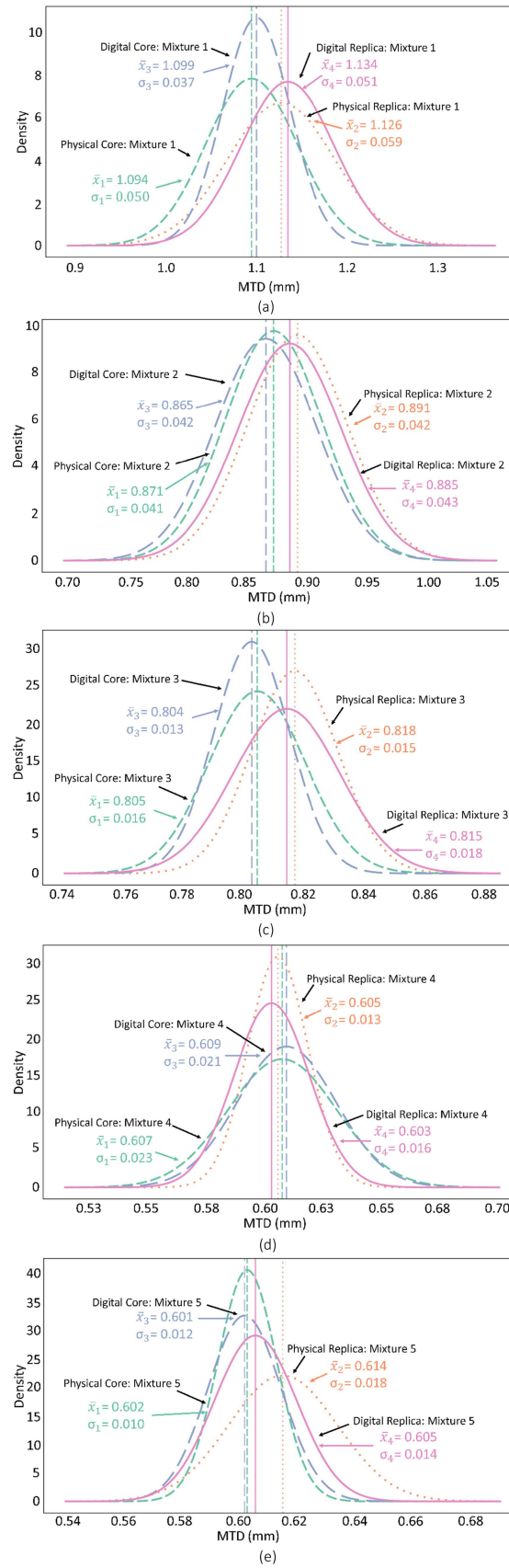


Figure 7. Gaussian distribution curves: (a) Mixture 1, (b) Mixture 2, (c) Mixture 3, (d) Mixture 4 and (e) Mixture 5.

‘Physical replica–Digital replica’. The relevant MTD values for the five samples were obtained by performing repeated MTD tests. This approach was adopted to reduce the risk of reaching incorrect conclusions caused by human error in the measurements. In addition to standard normality analysis (see Section 4.3), three distributional similarity tests of the Kolmogorov–Smirnov (KS) (An, 1933), Anderson–Darling (AD) (Anderson & Darling, 1954) and Cramér–von Mises (CvM) (Cramér, 1928) were used to compare MTD data across the different sets (see Table 3).

The KS test was employed to assess whether two datasets originated from the same underlying probability distribution. While the KS test was effective at detecting discrepancies near the central portion of the distribution, its sensitivity was found to diminish when differences occurred in the tails or among extreme values. To address this limitation, the AD test was used, as it places greater emphasis on the tails of the distribution. This focus was critical for identifying subtle differences caused by outliers or skewness that the KS test might have overlooked. In addition, the CvM test was applied to provide a more comprehensive evaluation of distributional similarities across the entire range of the data. Collectively, these tests were selected to ensure an unbiased comparison across all regions of the distribution, enabling reliable detection of differences in shape, scale and tail behaviour.

As given in Table 3, all three statistical tests for Mixture 1 yielded p values well above the typical significance threshold of 0.05 across all group comparisons. These results indicate a strong agreement between the respective MTD distributions. However, in a few cases, p -values were observed to be close to

Table 3. Distribution similarity assessment.

Mixture type	Group	Test	Statistics	p -value
Mixture 1	Physical core and physical replica	KS	0.2727	0.8326
		AD	0.5049	0.2055
		CvM	0.2045	0.2869
	Physical core and digital core	KS	0.1818	0.9971
		AD	0.3515	0.2500
		CvM	0.0909	0.6618
	Physical replica and digital replica	KS	0.2727	0.8326
		AD	0.5600	0.2500
		CvM	0.0744	0.7575
Mixture 2	Physical core and physical replica	KS	0.3636	0.4792
		AD	0.5201	0.2025
		CvM	0.2107	0.2704
	Physical core and digital core	KS	0.1818	0.9971
		AD	0.1134	0.2500
		CvM	0.0289	0.9971
	Physical replica and digital replica	KS	0.2727	0.8326
		AD	0.1376	0.2500
		CvM	0.0723	0.8127
Mixture 3	Physical core and physical replica	KS	0.5455	0.0747
		AD	5.1299	0.1031
		CvM	0.7810	0.2072
	Physical core and digital core	KS	0.2727	0.8326
		AD	0.2353	0.2500
		CvM	0.1426	0.4434
	Physical replica and digital replica	KS	0.3636	0.4792
		AD	1.7949	0.0591
		CvM	0.3864	0.0846
Mixture 4	Physical core and physical replica	KS	0.2727	0.8326
		AD	0.8375	0.2500
		CvM	0.1550	0.4135
	Physical core and digital core	KS	0.1818	0.9971
		AD	1.1359	0.2500
		CvM	0.0289	0.9971
	Physical replica and digital replica	KS	0.2727	0.8326
		AD	0.8077	0.2500
		CvM	0.1612	0.3879
Mixture 5	Physical core and physical replica	KS	0.4545	0.2115
		AD	2.4052	0.1335
		CvM	0.4112	0.0724
	Physical core and digital core	KS	0.0909	1.0000
		AD	1.2001	0.2500
		CvM	0.1269	0.9971
	Physical replica and digital replica	KS	0.3636	0.4792
		AD	1.4023	0.0858
		CvM	0.3017	0.1447

Table 4. Analysis of two-sample *t*-test.

Mixture type	Group	<i>p</i> value
Mixture 1	Physical core and physical replica	0.18
	Physical core and digital core	0.77
	Physical replica and digital replica	0.80
Mixture 2	Physical core and physical replica	0.25
	Physical core and digital core	0.69
	Physical replica and digital replica	0.75
Mixture 3	Physical core and physical replica	0.07
	Physical core and digital core	0.67
	Physical replica and digital replica	0.71
Mixture 4	Physical core and physical replica	0.72
	Physical core and digital core	0.85
	Physical replica and Digital replica	0.82
Mixture 5	Physical core and Physical replica	0.06
	Physical core and Digital core	0.21
	Physical replica and Digital replica	0.83

the threshold, suggesting minor deviations between datasets. The comparison between the Physical core and Digital core resulted in *p*-values of 0.9971 (KS), 0.2500 (AD) and 0.6618 (CvM), suggesting a high degree of similarity in both central tendency and overall distribution shape. Similar outcomes were observed in the comparisons involving the Physical replica, further reinforcing the distributional agreement between the physical and digital models.

A similar trend was observed for Mixture 2. All group comparisons resulted in *p*-values higher than the threshold, indicating strong similarity between the distributions. However, some *p*-values were relatively close to the significance threshold, suggesting minor deviations that may arise from inherent surface variability or measurement uncertainty. The Physical core–Digital core comparison yielded *p*-values of 0.9971 (KS), 0.2500 (AD) and 0.9971 (CvM), confirming that real MTD tests were done accurately. For Mixture 3, which was a relatively new dense asphalt sample, the KS, AD and CvM tests all produced *p*-values above 0.05. Although the AD and CvM tests yielded *p*-values that were closer to the significance threshold for the Physical core–Physical replica and Physical replica–Digital replica comparisons, these deviations remain within acceptable limits and do not affect the overall agreement between datasets.

Mixture 4 and Mixture 5, which were the rejuvenated ZOAB16 samples, all three tests produced *p*-values higher than the threshold value for every comparison. This confirmed that the smoother and more closed surface resulting from the rejuvenation treatment was captured reliably in both the physical and digital replicas. Furthermore, while comparing individual results, it was also observed that the results in-between the sets of Physical core–Physical replica, Physical core–Digital core and Physical replica–Digital replica were also representative in terms of macrotexture.

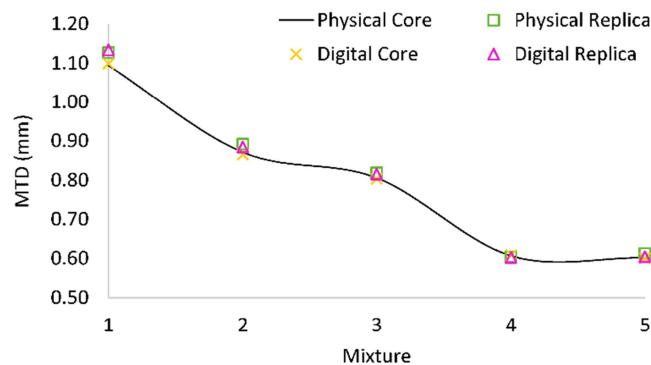
4.5. Comparative analysis of MTD using *t*-test and effect size

After confirming the normality and similarity of the data distributions across the groups of both mixtures using the tests presented in Section 4.4, further analyses were carried out to justify the comparison of mean MTD values between groups through parametric statistical methods. The KS, AD and CvM tests provide insight into overall distributional similarities-capturing differences in scale, shape and the presence of outliers. However, they cannot determine whether the average surface texture depths differed significantly between the Physical specimens and their replicas. Therefore, different tests are required. Two-sample *t*-tests were conducted to determine whether any statistically significant differences existed between the mean MTD values of the sets for all five samples. In parallel, Cohen's *d* effect size analysis was conducted to quantify the magnitude of mean differences independently of sample size.

In two-sample *t*-test, the null hypothesis (H_0) was proposed that there was no significant difference in the mean MTD between the two sets, while the alternative hypothesis (H_1) proposed a significant difference existed. As given in Table 4, all *p*-values were found to exceed the commonly used significance threshold of 0.05. This observation indicates that no statistically significant differences in mean MTD were detected across any of the set comparisons for either mixture. These results suggest that the physical and digital samples were comparable in terms of average surface texture depth.

Table 5. Analysis of Cohen's d test.

Mixture type	Group	Cohen's d value	Effect size
Mixture 1	Physical core and Physical replica	-0.596	Medium
	Physical core and Digital core	-0.123	Insignificant
	Physical replica and Digital replica	-0.131	Insignificant
Mixture 2	Physical core and Physical replica	-0.485	Medium
	Physical core and Digital core	+0.153	Insignificant
	Physical replica and Digital replica	-0.150	Insignificant
Mixture 3	Physical core and Physical replica	-0.556	Medium
	Physical core and Digital core	-0.125	Insignificant
	Physical replica and Digital replica	-0.172	Insignificant
Mixture 4	Physical core and Physical replica	+0.096	Insignificant
	Physical core and Digital core	-0.082	Insignificant
	Physical replica and Digital replica	-0.186	Insignificant
Mixture 5	Physical core and Physical replica	-0.412	Medium
	Physical core and Digital core	+0.082	Insignificant
	Physical replica and Digital replica	-0.153	Insignificant

**Figure 8.** Comparison of MTD values across the five mixtures.

However, statistical significance alone does not fully capture the practical relevance of the observed differences, particularly given the small to moderate sample sizes. Therefore, Cohen's d effect size was calculated to quantify the magnitude of the differences independently of sample size. As summarised in Table 5, the effect sizes for the comparisons between the Physical core and Physical replica ranged from medium ($d \approx -0.60$ for Mixture 1, $d \approx -0.49$ for Mixture 2, $d \approx -0.56$ for Mixture 3 and $d \approx -0.41$ for Mixture 5), suggesting a moderate increase in MTD for the Physical replicas relative to the Physical cores. In contrast, the effect sizes for the comparisons between the Physical core and Digital core, as well as between the Physical replica and Digital replica, were consistently small ($|d| < 0.2$), indicating negligible practical differences between the physical samples and their digital counterparts in all samples. Since this research is not concerned with whether a sample deviates in a positive or negative direction from the mean, the focus is solely on the magnitude of the deviation.

Figure 8 shows the agreement in MTD values across the five mixtures for all four sample types. The Physical core results show a clear decreasing trend in MTD from Mixture 1 to Mixture 5, and both the Physical replicas and the digital replicas follow this trend closely. The Physical replicas exhibit slightly higher MTD values in Mixtures 1, 2, 3 and 5, consistent with the medium effect sizes reported in Table 5, although these differences remain small relative to the overall trend. The near overlapping markers for the Digital core and Digital replica further demonstrate that the digital reconstructions captured the physical surface texture with high fidelity. Overall, the figure visually confirms the statistical findings, supporting the reliability of the digital samples for reproducing macrotexture characteristics.

Importantly, the decreasing MTD trend from Mixture 1 to Mixture 5 is also fully consistent with expectations based on mixture type and material conditioning. Mixture 1, representing the PA sample without rejuvenation, understandably exhibits the highest macrotexture depth due to its more open surface structure. In contrast, Mixture 5 corresponds to the rejuvenated PA sample, which is expected to have the lowest MTD as the rejuvenation process tends to soften the binder and promote aggregate reorientation or densification, reducing surface voids. The results in Figure 8 align with these established

behaviours seen in pavement engineering practice, further reinforcing the validity of both the measurement approach and the observed texture trends.

5. Conclusion

This research focused on developing and validating a methodology for replicating and assessing pavement surface texture geometry at the macro-texture level using both physical and digital approaches. The proposed methodology integrated MTD as a key 3D texture indicator, casting technology, automated random masking technique and smartphone video-based digital modelling using computer vision. The methodology was demonstrated using distinct asphalt mixtures with varying surface characteristics, and verification was performed using three additional randomly selected samples. Physical replicas were produced using silicone rubber casting and epoxy moulding, while digital replicas were generated using SfM techniques applied to smartphone-recorded videos. Validation of macro-texture geometry was carried out for both replica types using sand patch tests and the 3D geometric calculations. Comprehensive statistical analyses, including descriptive statistics, normality tests, variance homogeneity analysis and verification tests, were used to validate the results. The results showed that all samples of sets followed normal distributions with consistent data patterns. Based on the results and analysis presented in this paper, the following key conclusions can be drawn.

- I. MTD values calculated from sand-patch testing (physical) and 3D geometric calculations confirmed strong agreement between reference cores and their replicas. Absolute percentage errors remained below 7% in all cases, and statistical analyses (box plots, normality tests, distribution similarity tests, *t*-tests and effect size evaluation) indicated no statistically significant differences in most cases, with minor deviations observed in a few instances. These deviations fall within the expected range of measurement variability and do not affect the overall validity of the results. Hence, it could be concluded that both replication routes retained the macro-texture geometry with engineering-level accuracy.
- II. A random sampling and masking technique was introduced to replace traditional human-subjective visual comparison to avoid natural human biases. This automated method showed strong similarity between cores and replicas, eliminating interpretation bias and proving suitable for scalable surface validation.
- III. Based on the findings from the various statistical measurements, the digital cores and replicas consistently exhibited MTD distributions and mean values that were comparable to those of their physical counterparts. Cohen's *d* effect size analysis indicated only small to medium practical differences. This suggests that smartphone-based 3D reconstruction, when paired with appropriate post-processing, can provide digital surfaces of sufficient fidelity for pavement texture studies. The proposed methodology performed well across different varieties of pavement samples.

In general, it can be concluded that the proposed framework provides a validated pathway for conducting pavement surface studies in a controlled environment without depending solely on field testing. It enables cost-efficient, repeatable experimentation on pavement performance and supports the development of cloud-based systems for large-scale pavement monitoring. Future work could extend the current methodology by integrating additional 3D texture indicators (e.g., RMS, skewness, etc.) for a more complete surface geometry characterisation. Incorporating machine learning techniques could also automate texture classification and similarity assessments. Expanding the methodology to larger pavement sections and diverse surface types under real-world environmental conditions would help validate its robustness.

6. Limitations and future work

While the proposed methodology demonstrates strong potential for validating physical and digital pavement surface replicas at the macro-texture level, several limitations are acknowledged. The validation is primarily based on MTD as a macro-texture indicator, which, although practical and cost-effective, does not fully capture the complete three-dimensional complexity of pavement surface geometry. The study is

also limited to specific sets of pavement samples and mixture types, which may not fully represent the variability encountered in real-world conditions. In addition, the smartphone-video-based digital reconstruction approach is sensitive to factors such as lighting conditions, camera motion and image quality, which may influence the accuracy of the generated digital replicas. Although these factors were controlled as much as possible during testing, variations in data acquisition conditions may influence the quality of the reconstructed digital replicas. The current work focuses on geometrical validation, without explicitly assessing functional performance aspects such as friction, rolling resistance, or long-term mechanical behaviour of the replicas.

Although smartphone-video-based acquisition provides a practical and low-cost solution, extracted video frames may be affected by compression artefacts, motion blur and shutter-speed limitations. Future studies should investigate the use of high-resolution still-image acquisition to further improve reconstruction accuracy for precision-sensitive applications. Future research should focus on incorporating additional 3D texture parameters to provide a more comprehensive surface characterisation and extending the methodology to larger and more diverse datasets covering a wider range of pavement conditions. The integration of advanced computer vision and machine learning techniques could further enhance automation, classifications and accuracy in the validation process. Moreover, linking geometrical validation with functional pavement performance indicators would strengthen the practical applicability of the approach. The framework can also be further developed toward a cloud-based pavement monitoring system, enabling scalable and cost-effective surface assessment in real-world applications.

Acknowledgements

The authors gratefully acknowledge the support received from the Knowledge-based Pavement Engineering (KPE) research program. KPE is a collaborative initiative involving Rijkswaterstaat, TNO and TU Delft, aimed at advancing scientific and applied knowledge in the field of asphalt pavements. This research contributes to Rijkswaterstaat's ambitious objectives of achieving complete climate neutrality and embracing circular principles by 2030.

Author contributions

CRediT: **W. A. A. S. Premarathna**: Conceptualization, Data curation, Formal analysis, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing; **Anupam Kumar**: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing; **Fahim R. Khan**: Data curation, Investigation, Methodology, Resources, Writing – review & editing; **Maresh Moenielal**: Investigation, Project administration, Resources, Writing – review & editing; **Cor Kasbergen**: Data curation, Funding acquisition, Investigation, Project administration, Resources, Supervision, Writing – review & editing; **Sandra M. J. G. Erkens**: Funding acquisition, Investigation, Project administration, Supervision, Writing – review & editing.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The data are available from the authors upon reasonable request and with permission from the relevant authority.

References

- Al-Najati, I. A., Jasim, A. F., Chan, K. W., & Pung, S. Y. (2024). The future of tire energy: a novel one-end cap structure for sustainable energy harvesting. *Materials for Renewable and Sustainable Energy*, 13(2), 181–208. <https://doi.org/10.1007/s40243-023-00254-3>
- An, K. (1933). Sulla determinazione empirica di una legge di distribuzione. *Giornale dell'Istituto Italiano degli Attuari*, 4, 89–91.
- Andersen, L. G., Larsen, J. K., Fraser, E. S., Schmidt, B., & Dyre, J. C. (2015). Rolling resistance measurement and model development. *Journal of Transportation Engineering*, 141(2). [https://doi.org/10.1061/\(ASCE\)TE.1943-5436.0000673](https://doi.org/10.1061/(ASCE)TE.1943-5436.0000673)

- Anderson, T. W., & Darling, D. A. (1954). A test of goodness of fit. *Journal of the American Statistical Association*, 49(268), 765–769. <https://doi.org/10.1080/01621459.1954.10501232>
- ASTM International. (2015). *Standard test method for measuring pavement macrotexture depth using a volumetric technique* [Online]. <https://store.astm.org/standards/e965>
- Bajčičák, M., & Šuba, R. (2014). Study of thermal stress influence on dimensional stability of silicone molds. *Research Papers Faculty of Materials Science and Technology Slovak University of Technology*, 22(34), 15–19. <https://doi.org/10.2478/rput-2014-0022>
- Bergiers, A. (2011). *Comparison of rolling resistance measuring equipment-pilot study*.
- Biffi, A., Gobbi, M., & Mastinu, G. (2025). Tyre rolling resistance and tyre rolling loss: A theoretical and experimental study based on a new trailer. *Meccanica*, 60, 2561–2585. <https://doi.org/10.1007/s11012-025-01983-7>
- Bitelli, G., Simone, A., Girardi, F., & Lantieri, C. (2012). Laser scanning on road pavements: A new approach for characterizing surface texture. *Sensors*, 12(7), 9110–9128. <https://doi.org/10.3390/s120709110>
- Chen, B., Xiong, C., Li, W., He, J., & Zhang, X. (2021). Assessing surface texture features of asphalt pavement based on three-dimensional laser scanning technology. *Buildings*, 11(12), 623. <https://doi.org/10.3390/buildings11120623>
- Chen, J., Huang, X., Zheng, B., Zhao, R., Liu, X., Cao, Q., & Zhu, S. (2019). Real-time identification system of asphalt pavement texture based on the close-range photogrammetry. *Construction and Building Materials*, 226, 910–919. <https://doi.org/10.1016/j.conbuildmat.2019.07.321>
- Chen, S. (2022). A state-of-the-art review of asphalt pavement surface texture and its measurement techniques. *Journal of Road Engineering*, 2(2), 156–180. <https://doi.org/10.1016/j.jreng.2022.05.003>
- Clapp, T. G., & Eberhardt, A. C. (1986). Computation and analysis of texture-induced contact information in tire-pavement interaction. In *Transportation Research Record*, 1084, 23–29, Transportation Research Board, National Research Council, Washington, DC.
- Cramér, H. (1928). On the composition of elementary errors. *Scandinavian Actuarial Journal*, 1928(1), 13–74. <https://doi.org/10.1080/03461238.1928.10416862>
- D. T. Netherlands. 4TU.Federation. *4TU.ResearchData*. Retrieved September 23, 2025, from. <https://data.4tu.nl/>
- Dabous, S. A., Gacem, M. A., Zeiada, W., Hamad, K., & Al-Ruzouq, R. (2025). Artificial intelligence applications in pavement infrastructure damage detection with automated three-dimensional imaging – A systematic review. *Alexandria Engineering Journal*, 117, 510–533. <https://doi.org/10.1016/j.aej.2024.11.081>
- Dan, H. C., Long, Y., Yao, H., Li, S., Liu, Y., & Zhou, Q. (2023). Investigation on the fractal characteristic of asphalt pavement texture roughness incorporating 3D reconstruction technology. *Electronic Research Archive*, 31(4), 2337–2357. <https://doi.org/10.3934/era.2023119>
- Dan, H. C., Lu, B., & Li, M. (2024). Evaluation of asphalt pavement texture using multiview stereo reconstruction based on deep learning. *Construction and Building Materials*, 412, 134837. <https://doi.org/10.1016/j.conbuildmat.2023.134837>
- Das, A., & Mahanwar, P. (2020). A brief discussion on advances in polyurethane applications. *Advanced Industrial and Engineering Polymer Research*, 3(3), 93–101. <https://doi.org/10.1016/j.aiepr.2020.07.002>
- Descornet, G. (1990). Road-surface influence on tire rolling resistance, In *Surface characteristics of roadways: International research and technologies* (pp. 401–415). ASTM International. <https://doi.org/10.1520/STP23377S>
- Duan, Y., Yang, C., & Li, H. (2021). Low-complexity adaptive radius outlier removal filter based on PCA for lidar point cloud denoising. *Applied Optics*, 60(20), E1–E7. <https://doi.org/10.1364/AO.416341>
- Ejsmont, J., & Owczarzak, W. (2019). Engineering method of tire rolling resistance evaluation. *Measurement*, 145, 144–149. <https://doi.org/10.1016/j.measurement.2019.05.071>
- Ejsmont, J., Ronowski, G., Sommer, S., Owczarzak, W., & Berge, T. (2025). Replica road pavements for rolling resistance measurements. *Road Materials and Pavement Design*, 26, 2954–2964. <https://doi.org/10.1080/14680629.2025.2467401>
- Ejsmont, J., Ronowski, G., Ydrefors, L., Owczarzak, W., Sommer, S., & Świczko-Żurek, B. (2024). Comparison of tire rolling resistance measuring methods for different surfaces. *International Journal of Automotive Technology*, 25(4), 965–976. <https://doi.org/10.1007/s12239-024-00092-w>
- Fathi, H., El-Sayegh, Z., Ren, J., & El-Gindy, M. (2024). Modeling and validation of a passenger car tire using finite element analysis. *Vehicles*, 6(1), 384–402. <https://doi.org/10.3390/vehicles6010016>
- Gao, W., Zhang, Y., Ramanujan, D., Ramani, K., Chen, Y., Williams, C. B., Wang, C. C., Shin, Y. C., & Zavattieri, P. D. (2015). The status, challenges, and future of additive manufacturing in engineering. *CAD Computer Aided Design*, 69, 65–89. <https://doi.org/10.1016/j.cad.2015.04.001>
- Gao, X., Liu, Z., Zhang, H., Wu, S., Fan, W., & Zhang, G. (2025). Modeling and experimental study of tire rolling resistance based on rubber energy dissipation mechanism. *Experimental Techniques*, 49(5), 937–948. <https://doi.org/10.1007/s40799-025-00790-9>
- Gong, F., Cheng, X., Fang, B., Cheng, C., Liu, Y., & You, Z. (2023a). Prospect of 3D printing technologies in maintenance of asphalt pavement cracks and potholes. *Journal of Cleaner Production*, 397, 136551. <https://doi.org/10.1016/j.jclepro.2023.136551>
- Gong, F., Cheng, X., Wang, Q., Chen, Y., You, Z., & Liu, Y. (2023b). A review on the application of 3D printing technology in pavement maintenance. *Sustainability*, 15(7), 6237. <https://doi.org/10.3390/su15076237>
- Guessasma, S., Belhabib, S., & Nouri, H. (2019). Printability and tensile performance of 3D printed polyethylene terephthalate glycol using fused deposition modelling. *Polymers*, 11, 1220. <https://doi.org/10.3390/polym11071220>

- Hooghwerff, J., van Gils, E. W., & Reinink, H. F. (2013). Influence of road surface type on rolling resistance. Rijkswaterstaat, Ministry of Infrastructure and the Environment.
- Huang, C., & Huang, X. (2014). Effects of pavement texture on pavement friction: a review. *International Journal of Vehicle Design*, 65, 256–269. <https://doi.org/10.1504/IJVD.2014.060804>
- Huyan, J., Li, W., Tighe, S., Sun, Z., & Sun, H. (2020). Quantitative analysis of macrotexture of asphalt concrete pavement surface based on 3D data. *Transportation Research Record*, 2674(8), 732–744. <https://doi.org/10.1177/0361198120920269>
- ISO 13473-1-Characterization of pavement texture by use of surface profiles part 1 – : Determination of mean profile depth. International Organization for Standardization, Geneva, Switzerland.
- I. S. O. 13473-2. (2002). *Characterization of pavement texture by use of surface profiles–part 2: Terminology and basic requirements related to pavement texture profile analysis*. International Organization for Standardization.
- ISO 28580. (2009). *Passenger car, truck and bus tyres – Methods of measuring rolling resistance – Single point test and correlation of measurement results*.
- Jackson, R. J., Wojcik, A., & Miodownik, M. (2018). 3D printing of asphalt and its effect on mechanical properties. *Materials & Design*, 160, 468–474. <https://doi.org/10.1016/j.matdes.2018.09.030>
- Ji, X. P., Zhu, S., Sun, Y., Li, H., Chen, Y., & Chen, Y. (2024). Reconstruction and evolution of 3D model on asphalt pavement surface texture using digital image processing technology and accelerated pavement testing. *Road Materials and Pavement Design*, 25(8), 1694–1719. <https://doi.org/10.1080/14680629.2023.2268750>
- Jiang, R., Zhou, X., & Ran, M. (2024). 3D reconstruction and morphology analysis of coarse aggregate using optical laser triangulation and image processing technology. *Road Materials and Pavement Design*, 25(4), 790–819. <https://doi.org/10.1080/14680629.2023.2225637>
- Kazhdan, M., Bolitho, M., & Hoppe, H. (2006). Poisson surface reconstruction. In *Proceedings of the fourth eurographics symposium on geometry processing*. Eurographics Association.
- Kim, J. H., Kim, Y. K., Alalade, S., & Lee, S. W. (2025). Influence of pavement-texture condition on tire-pavement interaction noise. *KSCE Journal of Civil Engineering*, 29(5), 100109. <https://doi.org/10.1016/j.kscj.2024.100109>
- Knyaz, V. A., & Chibunichev, A. G. (2016). Photogrammetric techniques for road surface analysis. *Spatial Information Sciences – ISPRS Archives, International Society for Photogrammetry and Remote Sensing, XLI-B5*, 515–520. In *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. <https://doi.org/10.5194/isprsarchives-XLI-B5-515-2016>
- Le, M.-H., Cheng, C.-H., & Liu, D.-G. (2023). An efficient adaptive noise removal filter on range images for LiDAR point clouds. *Electronics (Basel)*, 12(9), 2150. <https://doi.org/10.3390/electronics12092150>
- Lei, J., Wang, E., Zeng, J., Wang, W., & Wu, J. (2014). Research of acquisition method for pavement surface texture based on photometric stereo techniques. In *17th International IEEE Conference on Intelligent Transportation Systems (ITSC)* (pp. 1596–1601). IEEE. <https://doi.org/10.1109/ITSC.2014.6957921>
- Leng, Z. (2023). Texturing and evaluation of concrete pavement surface: A state-of-the-art review. *Journal of Road Engineering*, 3(3), 252–265. <https://doi.org/10.1016/j.jreng.2023.08.001>
- Levene, H. (1960). Robust tests for equality of variances. *Contributions to probability and statistics*, 278–292), Stanford University Press.
- Levesque, W., Bégin-Drolet, A., & Lépine, J. (2023). Effects of pavement characteristics on rolling resistance of heavy vehicles: A literature review. *Transportation Research Record*, 2677(6), 296–309. <https://doi.org/10.1177/03611981221145125>
- Liang, H., Pagano, R. G., Oddone, S., Cong, L., & De Blasiis, M. R. (2024). Analysis of road surface texture for asphalt pavement adhesion assessment using 3D laser technology. *Remote Sensing*, 16(11), 1943. <https://doi.org/10.3390/rs16111943>
- Liu, Q., Pei, J., Wang, Z., Hu, D., Huang, G., Meng, Y., Lyu, L., & Zheng, F. (2024). Analysis of tire-pavement interaction modeling and rolling energy consumption based on finite element simulation. *Construction and Building Materials*, 425, 136101. <https://doi.org/10.1016/j.conbuildmat.2024.136101>
- Lo, S. H. (2002). Finite element mesh generation and adaptive meshing. *Progress in Structural Engineering and Materials*, 4(4), 381–399. <https://doi.org/10.1002/pse.135>
- Lou, Y., Lu, J. J., Chen, S., & Lang, H. (2022). A portable measurement system for pavement surface macrotexture – A case study in China. *International Journal of Pavement Engineering*, 23(12), 4136–4148. <https://doi.org/10.1080/10298436.2021.1935939>
- Mahmoudzadeh, A., Yeganeh, S. F., Arezoumand, S., & Golroo, A. (2020). 3D pavement surface reconstruction using an RGB-D sensor. In *6th International Electronic Conference on Sensors and Applications*, MDPI AG (p. 47). <https://doi.org/10.3390/ecsa-6-06641>
- Mashadi, B., Ebrahimi-Nejad, S., & Abbaspour, M. (2019). A rolling resistance estimate using nonlinear finite element numerical analysis of a full three-dimensional tyre model. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, 233(1), 147–160. <https://doi.org/10.1177/0954407018802733>
- Mechtcherine, V., Nerella, V. N., Will, F., Näther, M., Otto, J., & Krause, M. (2019). Large-scale digital concrete construction – CONPrint3D concept for on-site, monolithic 3D-printing. *Automation in Construction*, 107, 102933. <https://doi.org/10.1016/j.autcon.2019.102933>

- MIRIAM Project. (2010). *Models for Rolling Resistance in Road Infrastructure Asset Management Systems (MIRIAM): Publications*. Models for Rolling Resistance in Road Infrastructure Asset Management Systems Project. [Online]. <https://miriam-project.eu/Publications>
- Namjoo, M., & Golbakhshi, H. (2015). An efficient design tool based on FEM for evaluating effects of components properties and operating conditions on interaction of tire with rigid road. *Journal of Central South University*, 22(1), 189–195. <https://doi.org/10.1007/s11771-015-2509-7>
- OpenCV. *Open Source Computer Vision Library, 'OpenCV modules,' OpenCV 4.x Documentation* [online]. Retrieved October 16, 2025, from: <https://docs.opencv.org/>
- Owczarzak, W., Sommer, S., & Ronowski, G. (2024). Method of forming road surface replicas using 3D printing technology. *Coatings*, 14(11), 1455. <https://doi.org/10.3390/coatings14111455>
- Owczarzak, W., Sommer, S., & Ronowski, G. (2025). Analysis of the suitability of 3D-Printed road surface replicas for laboratory testing of rolling resistance. *Coatings*, 15(7), 766. <https://doi.org/10.3390/coatings15070766>
- Persson, J., Tiwari, A., Valbabs, E., Tolpekina, T., & Persson, B. (2018). On the use of silicon rubber replica for surface topography studies. *Tribology Letters*, 66, 140. <https://doi.org/10.1007/s11249-018-1092-0>
- Pomoni, M., & Plati, C. (2022). Skid resistance performance of asphalt mixtures containing recycled pavement materials under simulated weather conditions. *Recycling*, 7(4), 47. <https://doi.org/10.3390/recycling7040047>
- Pranjić, I., & Deluka-Tibljša, A. (2022). Pavement texture–friction relationship establishment via image analysis methods. *Materials*, 15(3), 846. <https://doi.org/10.3390/ma15030846>
- Pruitt, J. B., Clement, N. G., & Tapanila, L. (2016). Laser and structured light scanning to acquire 3-D morphology. *The Paleontological Society Papers*, 22, 57–69. <https://doi.org/10.1017/scs.2017.8>
- Qian, G., Wang, Z., Yu, H., Shi, C., Zhang, C., Ge, J., & Dai, W. (2024). Research on surface texture and skid resistance of asphalt pavement considering abrasion effect. *Case Studies in Construction Materials*, 20, e02949. <https://doi.org/10.1016/j.cscm.2024.e02949>
- Ramji, A., Grasso, M., Chase, J., Maqbool, H., Krypciak, M., Merchante, V., & Brighton, J. (2023). Implementation of a finite element modelling strategy for the prediction of aircraft tyre response. *Proceedings of the Institution of Mechanical Engineers. Part G, Journal of Aerospace Engineering*, 237(12), 2788–2800. <https://doi.org/10.1177/09544100231162659>
- Ran, M., Xiao, S., Li, M., Jiang, R., Zhou, X., & Tan, Y. (2024). Exploring the relationship between pavement mean texture depth and mean profile depth: from theoretical derivation to field results. *Surface Topography*, 12(2), 025028. <https://doi.org/10.1088/2051-672X/ad54dc>
- Ran, M., Xiao, S., Zhou, X., & Xiao, W. (2018). Evaluation of segregation in asphalt pavement surface using concave multifractal distribution. *Journal of Testing and Evaluation*, 46(5), 2100–2109. <https://doi.org/10.1520/JTE20160616>
- Roberts, R., Inzerillo, L., & Di Mino, G. (2020). Exploiting low-cost 3D imagery for the purposes of detecting and analyzing pavement distresses. *Infrastructures (Basel)*, 5(1), 6. <https://doi.org/10.3390/infrastructures5010006>
- Romeijn, T., Singh, K., Behrens, M., & Paul, G. (2021). Effect of accelerated weathering on the creep behaviour of additively manufactured polyethylene terephthalate glycol (PETG). *Journal of Polymer Research*, 28(9), 352. <https://doi.org/10.1007/s10965-021-02707-7>
- Ronowski, G. (2016). Design and calibration of rolling resistance test trailer R2Mk.2. *IOP Conference Series: Materials Science and Engineering*, 148, 012026. <https://doi.org/10.1088/1757-899X/148/1/012026>
- Sandberg, U. (2011). Rolling resistance: basic information and state-of-the-art on measurement methods. Final version. Swedish National Road and Transport Research Institute (VTI).
- Sandberg, U., Bergiers, A., Ejsmont, J. A., Goubert, L., Karlsson, R., & Zöller, M. (2011). *Road surface influence on tyre/road rolling resistance*.
- Sandberg, U. S. I. (1990). Road macro-and megatexture influence on fuel consumption. *Surface characteristics of roadways: International Research and Technologies*, 1031, 460.
- Schönberger, J. L., & Frahm, J.-M. (2016). *Structure-from-motion revisited* [Online]. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. <https://github.com/colmap/colmap>
- Schönberger, J. L., Price, T., Sattler, T., Frahm, J.-M., & Pollefeys, M. (2017). *A vote-and-verify strategy for fast spatial verification in image retrieval* [Online]. <https://github.com/vote-and-verify>
- Schönberger, J. L., Zheng, E., Frahm, J. M., & Pollefeys, M. (2016). Pixelwise view selection for unstructured multi-view stereo, *Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics)* (Vol. 9907, pp. 501–518). Springer. https://doi.org/10.1007/978-3-319-46487-9_31
- Sepahi, M., Abusalma, H., Jovanovic, V., & Eisazadeh, H. (2021). Mechanical properties of 3D-Printed parts made of polyethylene terephthalate glycol. *Journal of Materials Engineering and Performance*, 30, 6851–6861. <https://doi.org/10.1007/s11665-021-06032-4>
- Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika*, 52(3–4), 591–611. <https://doi.org/10.1093/biomet/52.3-4.591>
- Singh, S., & Singh, R. (2016). Precision investment casting: A state of art review and future trends. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 230(12), 2143–2164. <https://doi.org/10.1177/0954405415597844>

- Song, W. (2022). Correlation between morphology parameters and skid resistance of asphalt pavement. *Transportation safety and environment*, 4(1), tdac002. <https://doi.org/10.1093/tse/tdac002>
- Song, L., Guo, S., Niu, Y., Zhang, Y., Xia, H., & Li, X. (2025). Preparation and characterization of SBS/CR/LNBR composite modified asphalt for 3D printing applications. *Journal of Materials in Civil Engineering*, 37(5), <https://doi.org/10.1061/JMCEE7.MTENG-19449>
- Srirangam, S. K., Anupam, K., Kasbergen, C., Scarpas, A., & Cerezo, V. (2015). Study of influence of operating parameters on braking friction and rolling resistance. *Transportation Research Record*, 2525(1), 79–90. <https://doi.org/10.3141/2525-09>
- Sun, Z., Premarathna, W. A. A. S., Anupam, K., Kasbergen, C., & Erkens, S. M. J. G. (2024). A state-of-the-art review on rolling resistance of asphalt pavements and its environmental impact. *Construction and Building Materials*, 411, 133589. <https://doi.org/10.1016/j.conbuildmat.2023.133589>
- Świczko-Zurek, B., Ronowski, G., & Ejsmont, J. (2017). Tyre rolling resistance and its influence on fuel consumption. *Combustion Engines*, 168(1), 62–67. <https://doi.org/10.19206/ce-2017-110>
- Szutor, P., & Zichar, M. (2023). Fast radius outlier filter variant for large point clouds. *Data*, 8(10), 149. <https://doi.org/10.3390/data8100149>
- Tang, T., Anupam, K., Kasbergen, C., Kogbara, R., Scarpas, A., & Masad, E. (2018). Finite element studies of skid resistance under hot weather condition. *Transportation Research Record*, 2672(40), 382–394. <https://doi.org/10.1177/0361198118796728>
- Valvez, S., Silva, A. P., & Reis, P. N. B. (2022). Compressive behaviour of 3D-Printed PETG composites. *Aerospace*, 9(3), 124. <https://doi.org/10.3390/aerospace9030124>
- Wang, N., Dong, J., Fang, H., Li, B., Zhai, K., Ma, D., Shen, Y., & Hu, H. (2023). 3D reconstruction and segmentation system for pavement potholes based on improved structure-from-motion (SfM) and deep learning. *Construction and Building Materials*, 398, 132499. <https://doi.org/10.1016/j.conbuildmat.2023.132499>
- Wang, Y., Lai, X., Zhou, F., & Xue, J. (2020). Evaluation of pavement skid resistance using surface three-dimensional texture data. *Coatings*, 10(2), 162. <https://doi.org/10.3390/coatings10020162>
- Wickham, H., & Stryjewski, L. (2011). *40 years of boxplots*. Unpublished. <http://vitahad.co.nz/papers/boxplots.pdf>
- Zhu, L., Li, J., & Xiao, F. (2024). Carbon emission quantification and reduction in pavement use phase: A review. *Journal of Traffic and Transportation Engineering*, 11(1), 69–91. <https://doi.org/10.1016/j.jtte.2023.09.004>
- Zuniga-Garcia, N., & Prozzi, J. A. (2019). High-definition field texture measurements for predicting pavement friction. *Transportation Research Record*, 2673(1), 246–260. <https://doi.org/10.1177/0361198118821598>