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THRESHOLD SELECTION FOR THE BAYESIAN LOGISTIC LATENT VARIABLE MODEL OF HYPOGLYCEMIA SYMPTOM REPORTING CONSISTENCY

(*Pemilihan Ambang untuk Model Logistik Bayesian Berpemboleh Ubah Laten bagi Konsistensi Pelaporan Gejala Hipoglikemia*)

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ABSTRACT

Individual symptom patterns are unique, and consistent reporting of hypoglycemia symptoms is crucial for early detection and swift action. Symptoms occur when an individual's propensity combined with episode intensity exceeds a patient-specific threshold. Selecting an appropriate threshold form for consistency modeling is vital, as different forms can affect reporting patterns significantly. This study explores variations in symptom reporting consistency and precision using various threshold types and distributions within a logistic-type latent variable Bayesian model. The optimal threshold form is determined through analysis of real and simulated data, providing posterior estimates of consistency and precision values, along with Bayesian intervals and MCMC errors. This study examines five threshold forms: product, summation, interaction, sum of squared and square of product, along with two threshold distributions: Log-normal and Weibull. The square product threshold with a Log-normal threshold distribution proved most effective for modeling hypoglycemia symptom reporting consistency, achieving high specificity (83.76%) and strong negative predictive value (94.03%), but with moderate sensitivity (56.25%).

Keywords: hypoglycemia; symptom; Log-normal; Weibull; latent variable.

ABSTRAK

Corak simptom individu adalah unik, dan pelaporan simptom hipoglikemia yang konsisten adalah penting untuk pengesanan awal dan tindakan pantas. Gejala berlaku apabila kecenderungan individu digabungkan dengan intensiti episod melebihi ambang khusus pesakit. Memilih bentuk ambang yang sesuai untuk pemodelan konsisten adalah penting, kerana bentuk yang berbeza boleh menjejaskan corak pelaporan dengan ketara. Kajian ini meneroka variasi dalam konsistensi dan ketepatan pelaporan gejala menggunakan pelbagai jenis ambang dan taburan dalam model Bayesan pembolehubah pendam jenis logistik. Bentuk ambang optimum ditentukan melalui analisis data sebenar dan simulasi, memberikan anggaran posterior nilai ketekalan dan ketepatan, bersama-sama dengan selang Bayesian dan ralat MCMC. Kajian ini mengkaji lima bentuk ambang—hasil, penjumlahan, interaksi, jumlah kuasa dua dan kuasa dua produk—dan dua taburan ambang: Log-normal dan Weibull. Pemodelan konsistensi simptom hipoglikemia ditunjukkan sebagai paling berkesan apabila menggunakan bentuk ambang hasil darab ambang kuasa dua dengan taburan ambang Log-normal.

Kata kunci: hipoglikemia; gejala; Log-normal; Weibull; pembolehubah terpendam.

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Threshold Selection for the Bayesian Logistic Latent Variable Model of Hypoglycemia Symptom Reporting

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